

The Role of Social Network Sites in Creating Information Value and Social Capital

D I S S E R T A T I O N

zur Erlangung des akademischen Grades doctor rerum politicarum

(Doktor der Wirtschaftswissenschaft)

eingereicht an der

Wirtschaftswissenschaftlichen Fakultät

der Humboldt-Universität zu Berlin

von

Ksenia Koroleva

Präsident der Humboldt-Universität zu Berlin:

Prof. Dr. Jan-Hendrik Olbertz

Dekan der Wirtschaftswissenschaftlichen Fakultät:

Prof. Dr. Ulrich Kamecke

Gutachter/Gutachterin:

1. Prof. Oliver Günther, PhD

2. Prof. Gerald C. Kane, PhD

Tag des Kolloquiums:

23.08.2012

Contents

List of Tables.....	v
List of Figures	vii
List of Abbreviations.....	viii
Summary.....	ix
Zusammenfassung.....	x
A Introduction	1
1 Social Network Sites as a New Form of Computer-Mediated Communication.....	1
1.1 Definition: Social Network Sites (SNS).....	1
1.2 Functionality of SNS.....	2
1.3 SNS as Communication Medium.....	4
2 The Main Concepts	6
2.1 Network Structural Properties	6
2.2 Information Characteristics.....	8
2.3 Experience with SNS	11
3 Theoretical Framework of the Dissertation.....	13
3.1 Aligning the Research Questions.....	13
3.2 The Generic Model	16
4 Methodological Introduction	19
B Information Characteristics and Information Value.....	23
1 Introduction	23
2 Qualitative Study	24
2.1 Theoretical Background.....	24
2.2 Methodological Approach	25
2.3 Conceptual Model.....	26
2.4 Discussion	31
3 Empirical Studies	32
3.1 Theoretical Background.....	32
3.2 Study and Application Design B1 & B2	36
3.3 Descriptive Statistics.....	38
3.4 Model B1: Impact of Social Information on Information Value.....	41

3.5	<i>Model B2: Impact of Contextual Information on Information Value</i>	57
4	Algorithm Design and Evaluation	67
4.1	<i>Theoretical Background</i>	68
4.2	<i>Input Factors</i>	69
4.3	<i>Methodological Approach</i>	71
4.4	<i>Computational Results</i>	72
4.5	<i>Discussion</i>	77
5	Conclusion	78
C	Network Construction and Network Structure	82
1	Introduction	82
2	Network Construction Behavior	84
2.1	<i>Theoretical Background</i>	84
2.2	<i>Qualitative Study</i>	86
2.3	<i>Empirical Study</i>	94
2.4	<i>Discussion</i>	98
3	Network Structure and Information Value	100
3.1	<i>Theoretical Background</i>	101
3.2	<i>Research Model and Hypotheses (C2)</i>	104
3.3	<i>Application and Study Design C2</i>	110
3.4	<i>Empirical Operationalization</i>	111
3.5	<i>Descriptive Statistics</i>	112
3.6	<i>Estimation Results</i>	115
3.7	<i>Discussion</i>	117
4	Conclusion	119
D	The Process of Social Capital Formation on Social Network Sites	123
1	Introduction	123
2	Theoretical Background	124
3	Qualitative Study	126
3.1	<i>Methodological Approach</i>	126
3.2	<i>Conceptual Model</i>	127
4	Empirical Study	133
4.1	<i>Study Design</i>	133
4.2	<i>Identification of Dimensions</i>	134
4.3	<i>Research Models and Hypotheses</i>	135

4.4	<i>Estimation Results</i>	136
4.5	<i>Discussion</i>	141
5	Conclusion.....	143
E	Concluding Remarks	146
F	References	x
G	Appendix	xxiv
	Acknowledgements	xxxv
	Selbstständigkeitserklärung	xxxvi

List of Tables

Table 1	Typology of SNS Use	12
Table 2	Aligning the Research Questions	15
Table 3	Peer-reviewed Publications included in the Dissertation	18
Table 4	Methodological Approaches of the Dissertation	20
Table 5	Information Characteristics as Sources of Information Overload	28
Table 6	Network Characteristics as Sources of Information Overload	29
Table 7	Frequency Distribution of Information Evaluations	37
Table 8	Frequency Distribution of the Behavioral Intention	38
Table 9	Frequency Distribution of Tie Strength	39
Table 10	Summary Statistics for Information Characteristics	39
Table 11	Frequency Distribution of Communication Intensity	40
Table 12	Frequency Distribution of Posting Frequency	40
Table 13	Estimation Results of Model B1	53
Table 14	Convergent Validity of Constructs in Model B2	63
Table 15	Discriminant Validity of Constructs in Model B2	64
Table 16	Estimation Results of Model B2 (information value)	65
Table 17	Estimation Results of Model B2 (behavioral intention)¹¹	66
Table 18	Algorithm Input Factors	70
Table 19	Possible Algorithm Designs	72
Table 20	Mean Absolute Error Classification Accuracy	75
Table 21	Quality Criteria of Constructs for Model C1	96
Table 22	Estimation Results of Model C1	97
Table 23	Categorization of Ties on SNS	103
Table 24	Descriptive Statistics of Model C2	113
Table 25	Pairwise Tetrachoric Correlations	114
Table 26	Tie Strength vs. Network Overlap	115
Table 27	Estimation Results of Model C2	116
Table 28	Convergent Validity of Constructs in Models D1 and D2	137

Table 29	Discriminant Validity of Constructs in Model D2	138
Table 30	Estimation Results of the Direct Model (D1)	139
Table 31	Estimation Results of the Mediated Model (D2)³³	139
Table 32	Effect sizes and Sobel Test Statistics for Model Mediators	141

List of Figures

Figure 1 Typology of Ties on SNS	3
Figure 2 Main CMC Theories	5
Figure 3 Levels of Network Analysis	7
Figure 4 The Generic Framework	17
Figure 5 Conceptual Model of Information Overload on SNS	27
Figure 6 Research Model B1	43
Figure 7 Methodological Approach of Model B1	50
Figure 8 Composite coefficient and number of ratings at levels of tie strength	54
Figure 10 Research Model B2	58
Figure 11 Classification Accuracy in two classes	73
Figure 12 Classification Accuracy in three classes	73
Figure 13 Classification Accuracy in six classes	74
Figure 14 Frequency of Similarity vs. Tie Strength	75
Figure 15 Frequency of Communication Intensity vs. Tie Strength	76
Figure 16 Distribution of the Ranking Accuracy	77
Figure 17 Process Model of Handling Friendship Requests	88
Figure 18 Research Model C1	94
Figure 19 Research Model C2	104
Figure 20 Frequency distributions of Model Variables in Study C2	113
Figure 21 Conceptual Model of Social Capital Formation on SNS	127
Figure 22 Research Model D1 (direct)	135
Figure 23 Research model D2 (mediated)	136

List of Abbreviations

General Terms:

SNS – Social Network Sites

FB - Facebook

Sender – is the person who is sharing information on SNS

Receiver – is the person who is receiving and/or evaluating information

CMC – Computer-Mediated Communication

FtF – Face-to-Face Communication

FR – Friendship Request

IO – Information Overload

Theories:

TRA - Theory of Reasoned Action

TAM - Technology-Acceptance Model

GT – Grounded Theory

SNA – Social Network Analysis

Models:

B1 – Impact of Social Information on Information Value

B2 – Impact of Breadth, Depth and Contextual Information on Information Value

C1 – Impact of Benefits, Costs and Social Environment on Network Expansion

C2 – Impact of Network Structure on Information Value

D1 – Impact of types of SNS use on Social Capital Benefits

D2 – Impact of Shared Information and Network Structure on Social Capital Benefits

Methodological Terms:

EFA – Exploratory Factor Analysis

SEM – Structural Equation Modeling

PLS – Partial Least Squares

PCA - Principal Component Analysis

OLS - Ordinary Least Squares

GLS - Panel-Generalized Least Squares

CR - Composite Reliability

CA - Cronbach's Alpha

AVE - Average Variance Extracted

MAE – Mean Absolute Error

VIF – Variance Inflation Factors

NN – Neural Network Algorithm

Data collection:

Q – Interview Quotation

API – Application Programming Interface

Summary

As SNS users gain experience with using SNS they: i) exchange the information with each other; ii) connect with each other and form certain network structures as a result; iii) obtain the social capital benefits due to the maintenance of relationships with others. The dissertation structure clearly reflects these peculiarities of SNS. Thus, in the first part of the dissertation we explore the impact of information characteristics – depth, breadth, context, social information – on the value of information users derive from their networks. In the second part of the dissertation we explore how users construct their networks and how properties of network structure –tie strength and network overlap– relate to information value. In the third part, we explore the impact of network structure and shared information in the process of social capital formation. We additionally control for the user experience, as we believe that this factor might impact the perception of value on SNS.

The dissertation is based on several theoretical frameworks: i) social network analysis; ii) IS theories of e.g. media richness, social presence, social influence; iii) psychological theories of attitude formation, which determine what are the peculiarities of SNS and how to study them. In methodological terms we can distinguish between quantitative and qualitative approaches. Due to the scarcity of research findings we use explorative methodologies, such as Grounded Theory to study these new phenomena and generate conceptual models. These models are then verified empirically. Although most of the research presented in this dissertation is behavioral, we can also recognize design science elements. For example, we design and implement Facebook applications that allow to collect user data in real time.

The main results of the dissertation can be summarized around three major contributions. First and foremost, the underlying tie strength emerges as the most important factor that drives user behavior on SNS. Second, although people prefer information from their stronger ties, researchers should differentiate between different forms of network structure in their impact on information value, as, for example, network overlap has a negative relationship with information value. Third, experience factors mediate many of the behaviors of users on SNS.

Zusammenfassung

Wenn die Nutzer Erfahrungen mit Sozialen Netzwerken sammeln: i) tauschen sie Informationen mit einander aus; ii) verbinden sich mit einander und bilden Netzwerke; und iii) können auf soziales Kapital zugreifen, das durch die Pflege von diesen Kontakten entsteht. Die Struktur dieser Dissertation spiegelt diese drei Besonderheiten wider. In dem ersten Kapitel untersuchen wir den Einfluss von Informationseigenschaften – den Umfang, die Tiefe, den Kontext als auch dem Feedback– auf den Informationsnutzen. Im zweiten Kapitel untersuchen wir die Netzwerk-Gestaltungsstrategien und die Beziehung von den resultierenden Netzwerkeigenschaften – die Beziehungsstärke als auch Netzwerküberschneidung – mit dem Informationsnutzen. Im dritten Kapitel erforschen wir den Einfluß von den gewonnenen Informationen und der Struktur des Netzwerkes – auf das Soziale Kapital. Zusätzlich beziehen wir in jedes Kapitel die Erfahrung der Nutzer mit dem Medium ein.

Die Dissertation beruht auf folgenden theoretischen Ansätzen: i) soziale Netzwerkanalyse; ii) Theorien der Wirtschaftsinformatik, u.a. Medien-reichhaltigkeitstheorie, Sozialpräsenztheorie, und Sozialeinflusstheorie; iii) sozialwissenschaftliche Verhaltenstheorien, welche die Besonderheiten von Sozialen Netzwerken zu identifizieren und Ansätze zu deren Analyse zu entwickeln erlauben. Aufgrund von fehlenden Forschungserkenntnissen, setzen wir Grounded Theory ein, um konzeptionelle Verhaltensmodelle zu entwickeln. Diese Modelle werden im Anschluß empirisch getestet. Obwohl die Forschung in dieser Dissertation meist verhaltenswissenschaftlich ist, kann man auch Ansätze aus der Design Science erkennen. Zum Beispiel, spezielle Facebook-Anwendungen sind implementiert um reale Nutzerdaten zeitnah zu sammeln.

Diese Dissertation weist drei Hauptergebnisse auf. Erstens, die Beziehungsstärke ist der wichtigster Faktor, der das Verhalten von den Nutzern bestimmt. Zweitens, obwohl die Nutzer die Informationen von Ihren engen Freunden bevorzugen, andere Netzwerkeigenschaften sollten in Betracht gezogen werden, denn zum Beispiel Netzwerküberschneidung einen negativen Einfluss auf Informationsnutzen hat. Drittens, Erfahrungsfaktoren beeinflussen das Nutzerverhalten auf diesen Netzwerken.

A Introduction

1 Social Network Sites as a New Form of Computer-Mediated Communication

1.1 Definition: Social Network Sites (SNS)

The most frequently cited work of boyd and Ellison (2008) defines SNS as “*web-based services that allow individuals to: 1) construct a public or semi-public profile; 2) articulate a list of other users with whom they share a connection; and 3) view and traverse their list of connections and those made by others within the system*” (boyd and Ellison, 2008, p. 211). The authors specifically refer to these new types of networks as social network sites, as they argue that the term ‘networking’ (which is also frequently used when referring to these new media) focuses on connecting unknown people with each other, whereas the main purpose of SNS such as Facebook is rather to connect people with an already established relationship (boyd and Ellison 2008). Moreover, authors want to encompass all types of networks that might have other purposes than only networking. However, putting all social media applications under one umbrella might lead to missing out on certain dynamics when studying these new phenomena (Beer 2008). For example, YouTube is more focused on entertainment and content sharing, whereas LinkedIn has a clear networking orientation. This dissertation focuses on studying SNS on the example of Facebook, the main purpose of which is to connect people with each other and allow them to share information.

The definition of SNS mentioned above was coined right after Facebook which by now boasts an astonishing number of 900 million users (Facebook 2012) has opened up for general public in 2006. Since that time SNS have undergone a great deal of development and the functionality has changed considerably. Additionally, adoption spread to other population groups and countries and with it, the purposes and motivations of use have broadened. For example, in their early age SNS centered around the profiles that displayed a list of friends with whom a user is connected– it was what the user saw upon log-in and that connected to the information shared by others. As such the main activity included “*traversing the network graph by clicking through friends lists*” (boyd and Ellison 2008, p. 213). Although the connections of a user to others are a vital element of SNS nowadays as well, they constitute rather a backbone of SNS. Some of these friend lists are not even public and the activity is centered around the information and interactions on the Newsfeed, where not only user’s friends – but also broader circles of friends of friends are visible. Therefore the definition should be extended to account for the focus of functionality to interact and share information with others.

Moreover, although the connections on SNS are referred to as ‘friends’, boyd and Ellison (2008) recognize that it is a different type of relationship than what is colloquially referred to as friend. At the same time, they stress that these networks are aimed at connecting individuals that know each other rather than initiating new connections. That is, authors recognize that SNS offer a new type of connection, but they

do not make it clear how this connection is related to the existing relationships of users. By now SNS are fully integrated into the lives of users and their role for existing relationships needs to be defined. SNS can be treated from the constructivist or realist perspective (Kane et al. 2012). The realist perspective suggests that SNS is simply another tool to support the existing relationships and to provide additional ways to interact and exchange information. In contrast, the constructivist perspective views SNS as providing new relationships and behaviors, determined by the functionality of SNS. Specifically, friendship on SNS is a new kind of relationship which can co-exist with and impact the real-life relationship. The recent developments of SNS reflect this dualism: not only people shape a certain technology, but also technology shapes the behavior of users. This is illustrated by such new forms of behavior as “liking”, constructing a desired image of oneself in the profile, as well as traversing the history of interactions with others in the timeline. These SNS enabled features may affect how individuals view themselves, relate to others and behave in the real world.

SNS offer completely new environments with a lot of new features the impact of which on the relationships and interactions of users still remains unclear. That is, do these networks bring about real benefits to its users? If so, how can these benefits be gained? And what is the explicit role of SNS in this process? That is, do users get more social capital now that all the information is easily accessible and saved? Or do they feel overloaded by the constant information updates provided by the members of their broad networks? Now that the networks are visualized, can users better estimate the abilities and the knowledge that others have? Would users more eagerly add friends from childhood or those contacts that might prove useful in the future? These questions will be addressed in the dissertation.

1.2 Functionality of SNS

SNS offer distinct features that allow to support different types of activities. Social Network Analysis distinguishes four basic types of ties: similarities, social relations, interactions and flows, which form a networking cycle as depicted in Figure 1 (Borgatti et al. 2009). According to this cycle, proximities and/or similarities help form social relationships, which are developed during the interactions in which different resources flow (Borgatti et al. 2005). Previous CMC communication (such as E-mail) supported only one type of ties – interactions, whereas as the definition of SNS suggest – they are specifically designed to support personal relations and as the recent developments show information flows as well. Moreover, SNS distort the continuum by supporting information flows without interactions and enable interactions without an established connection (Kane et al. 2012).

The main function of SNS is to support different types of *relations*. For example, SNS help to find lost acquaintances (and thus reactivate ties which would otherwise have been lost), establish a connection with someone recently met (and thus overcome the awkwardness of the necessity to exchange phone numbers), as well as connect with unfamiliar people based on shared interests, mutual friends or simply because of an attractive profile (Krasnova et al. 2010c). The relationships that the person maintains with others can help other users infer information about this person and induce trust in the virtual identity of

the person. Already the number of friends may provide certain indices: very few friends linked to the profile of the user might cause distrust, whereas overabundance of friend connections may signal behaviors known as ‘collecting’ (Donath and boyd 2004) and have an adverse impact on user popularity (Tom Tong et al. 2008). At the same time, the number of mutual friends indicates the interconnectedness of user’s networks or belongingness to certain friend circles.

SNS offer users different ways to *interact* with others. As opposed to other forms of CMC communication, such as e-mail or blogs that support just one type of interactions, users on SNS can choose to communicate either publicly by broadcasting their information to all the members of their network simultaneously or privately to specific people, synchronously by using the possibilities of an integrated chat or asynchronously through the stream (Sandberg 2009). Public communication is advantageous in the sense that it reduces the costs of acquiring information and ensures the simultaneous access to the resources of others. Another feature is that interactions can also occur between users who are not directly connected with each other through the stream communication with the outer circles of their friends. Such interactions can promote the development of new relationships and thus reverse the cycle presented in Figure 1.

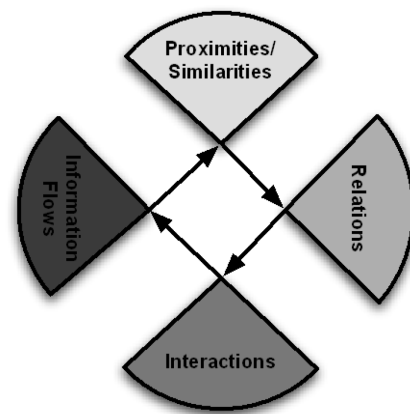


Figure 1 **Typology of Ties on SNS**

As a result of interactions, *information* is an important resource that flows between the users on SNS and triggers new interactions as well as subsequent connections and relationship development. As opposed to previous generations of CMC, SNS allow to exchange much richer information (such as pictures, links, videos, etc.) and tailor information to its recipients, for example by limiting the access to information to specific groups of users or tagging particular users. Undermining the traditional assumptions of SNA theory, SNS enables information to flow between users without interaction (when the information is shared by others on the Newsfeed) or without being connected to each other (when users interact through a mutual acquaintance in a stream) (Kane et al. 2012).

Finally, SNS aims at supporting *proximities and similarities* as well. In fact, by connecting people at different geographical distances, they undermine this prerequisite for social relations. At the same time, the newly emerging location-based SNS connect people based on their physical location. Users tag themselves at different places, informing their friends about their current location and thus make it possible to

meet those they already know or new acquaintances in the same location. Additionally, SNS offer the possibilities for people to connect based on their shared interests. For example, artists and companies are encouraged to create pages and post information for their fans, who can interact with it, and thus get to know each other, and based on these similarities develop a relationship.

In this dissertation we explore these distinct features of SNS, specifically: the characteristics of information flows, the networks of users which are formed as a result of the maintenance of the relationships with others, and the experience in interactions of users on the network. However, the more users connect with each other and interact on the platform, the more information is exchanged on the platform. As users are bounded in their cognitive abilities, they need to adopt strategies to cope with the incoming information in order to avoid information overload (Koroleva et al. 2010). Therefore, we aim to identify which factors contained in the information itself, the relationships that users maintain and the interactions they have on the platform induce users to pay attention to the information transmitted by their networks of relationships with others on SNS.

1.3 SNS as Communication Medium

Researchers have been trying to evaluate communication media based on the characteristics they possess, such as: richness, interactivity, ability to promote the sense of presence of the people involved in communication and the availability of social context cues that assist in the interpretation of information. We use the theories – social presence, media richness, social context cues – to evaluate SNS as a new communication medium. As presented in Figure 2, these theories point to the same causes and effects regarding the impact of contextual cues and the immediacy of feedback on the type of information that is transmitted and the subsequent possibility of relationship development. Due to its ability to transfer less cues in general and less social information in particular as well as exhibit significant delays in feedback previous forms of CMC (such as E-mail) are considered less rich than FtF communication (e.g. Walther 1995) and therefore exchanges through it can only be beneficial for sharing less complex and rather objective information (Daft and Lengel 1986). However, SNS as the new form of CMC are able to overcome many of these limitations.

First, media richness, defined as the ability of information to provide understanding within a time interval, is largely determined by: the ability of the medium to transmit multiple cues, immediacy of feedback, language variety and personalization (Daft and Lengel 1986). Media richness stresses the role of the immediacy of feedback – the extent to which a medium enables users to give rapid feedback on the information they receive (Daft and Lengel 1986) – which plays the role of informing the sender that the receiver has either understood the message or requires additional information. By minimizing the time required to achieve understanding, immediacy of feedback allows to communicate more quickly and effectively and thus increases the richness of a medium (Dennis and Kinney 1998). In traditional communication, two types of feedback are distinguished: concurrent and sequential. Concurrent feedback is provided simultaneously with the message and takes the form of non-verbal gestures or short messages, whereas sequen-

tial feedback occurs when the receiver responds more elaborately (Dennis and Kinney 1998). CMC, such as E-mail, are considered quite lean media, as they evidence significant delays in providing feedback (e.g. Daft and Lengel 1986). SNS, on the other hand, allow users to provide feedback through ratings and comments, the public nature of which ensures that feedback is delivered quite rapidly, as there is always someone in the network who has not understood the message and wants to clarify it (or approve it in an inverse case). Thus, SNS provide richer media for information exchange than traditional forms of CMC.

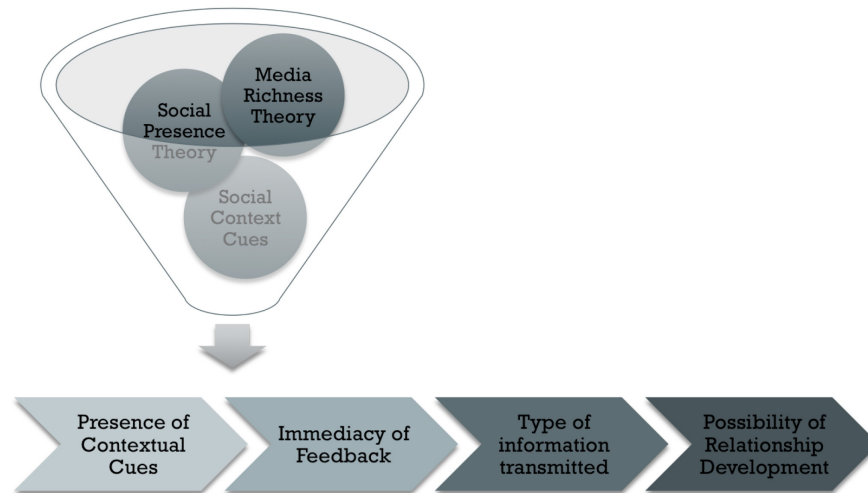


Figure 2 **Main CMC Theories**

Second, social presence, defined as the degree to which a medium facilitates the awareness of the other person during the interaction and the consequent interpersonal relationships is helpful for the formation of shared meaning (Short et al. 1976, Fulk et al. 1990, Yoo and Alavi 2001). Here the multiplicity of information cues - or the number of ways in which information can be communicated, such as text, verbal and nonverbal cues (Daft and Lengel, 1986) – is stressed. Media with fewer cues are less friendly, more impersonal and even depersonalizing (Walther 1992, Sproull and Kiesler, 1986) and therefore can only be used for communicating simple information (Dennis and Kinney 1998) and can impede relationship development (Walther 1995). Online environments are often accused of the lack of cues, such as the ability to draw inferences from the sender’s facial expression or mode of dress that assist in interpretation of especially tacit information – information that is difficult to put into words (Dellarocas 2003). Although SNS does not provide non-verbal cues as they are commonly referred to, it transmits a lot of contextual information on the profiles of the users, revealed during communication with others, as well as provides for the interactivity of the media (by tagging others, posting pictures and videos) and thus increases the sense of presence of others when interacting on the network.

Third, authors stress the role of a broader social context in transmitting relational information necessary for interpersonal communication (Walther 1992). Although several dimensions of social context are important, situational context cues – “features of the immediate communication situation” – are most salient for subsequent relationship development (Sproull and Kiesler 1986). The features of the immediate com-

munication situation usually include the relationship among senders and receivers, the topic of communication and the norms and conventions that define the nature of the social situation (Walther and Burgoon 1992, Sproull and Kiesler 1986). Because CMC (E-mail) possesses minimal social context cues and no relational information, it has been found to result in more impulsive and less socially differentiated behavior which inhibits relationship development (Sproull and Kiesler 1986). In contrast, SNS offers norms and values that encourage communication with unknown others, connecting to those one barely knows and thus developing new relationships.

Summarizing, due to its ability to provide different types of feedback as well as transmit a myriad of contextual cues, we propose that in terms of richness and social presence SNS communication can be well placed between FtF and traditional CMC (such as E-mail) on the information richness continuum. Therefore, users are able to exchange much richer, rather subjective and also tacit information through this medium more effectively and thus are able to enhance the relationships that they maintain with others on the network. Recognizing these enhanced abilities of SNS to transfer information, we would like to explore how users value this information and how does it relate to other benefits that users can obtain from their networks.

2 The Main Concepts

The functionality and peculiarities of SNS described in section 1.3 stress the role of the following factors, which are extensively explored in the dissertation: i) the networks of users that form as a result of their relationships with each other; ii) the content that flows between users in the network; iii) the experience of users with the medium and in interactions with others. In this dissertation we study not only how these aspects form, but also analyze what impact do they have on the ability to obtain benefits of social capital. Moreover, the analysis is carried out on both macro- vs. micro levels, with respect to:

- whether it refers to the relationship between two users or also includes other users in the network;
- whether it refers only to the specific content that is shared or to all the content shared on the platform;
- whether it relates to experience with the medium in general or experience in communicating with specific users.

2.1 Network Structural Properties

As discussed in section 1.2 the main function of SNS is to support the relations between people. These relationships can be productive in the sense that they link the person to the resources that others possess (Bourdieu 1985). Therefore, one might think that the more relations people form with each other, the higher is their social capital – the ability to take advantage of the resources when needed (Resnick 2001). However, not all equally sized networks result in the same amount of benefits. These largely depend on

the structure of the relationships between users, the configuration of their overall network and the position of the user in it (Burt 1992). Thus, in order to estimate the amount of benefits that accrues to the users, one has to measure the properties of a network structure. Researchers in the area of Social Network Analysis (SNA) usually study the configurations of individuals' networks on three different levels, as depicted in Figure 3: (i) at the network level by analyzing the structure, measured by e.g. network density or shape; (ii) at the dyad level by studying the relationship between two people, where their relationships differ by strength or type; (iii) at the node level by estimating the structural position of a person, with the help of e.g. a centrality measure (Borgatti et al. 2009).

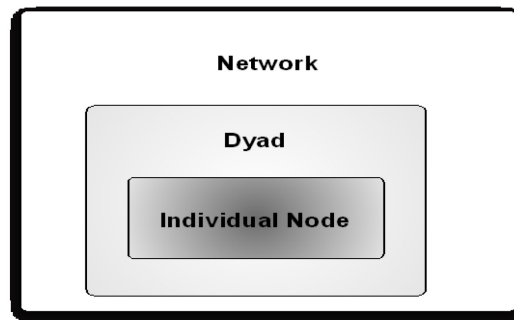


Figure 3 Levels of Network Analysis

On the *network level* of analysis density shows the level of connectedness between the people in the network. Researchers argue whether a sparse or a dense network is more beneficial. On the one hand, a highly dense network provides easy access to each other's resources, facilitates trust and diminishes risk of opportunism (Coleman 1988). However, people in such networks tend to possess the same information, which is redundant. On the other hand, in a rather sparse network the probability that people possess non-redundant information is higher and thus provide each other with complementary informational benefits (Burt 1992). Especially a network rich in *structural holes* – bridges to otherwise disconnected groups of people – is positively associated with such benefits as job placement, promotion, creativity, innovation, productivity and performance (e.g. Uzzi 1997; Hansen 1999, 2002).

On the *dyad level* of analysis, the relationship between two people is assessed. *Tie Strength* is a direct measure of the direct relationship between two people. Whether weak or strong ties are more beneficial has been a major debate among researchers. As weak ties usually connect people from otherwise diverse groups, they are associated with better job searches (Granovetter 1973), team performance (Reagans and Zukerman 2001), academic output (Swedberg 1990), success of social movements (Centola and Macy 2007), etc. The advent of IT-enabled communication networks (E-mail) lead the researchers to believe that weak ties have more value in these networks (Constant et al. 1996, Pickering and King 1995). At the same time, weak ties are typically opportunistic, functional and only selfishly cooperative (Granovetter 1973, Uzzi 1997). Strong ties, on the other hand, are more willing to share information and to devote their time to assist one another thus creating a favorable environment for information transfer (Coleman 1988,

Uzzi 1996). Moreover, strong ties possess knowledge about who knows what and requires which information and therefore are more valuable in exchanging information (Uzzi 1997, Hansen 1999).

On the *node level* the position of the tie in the network is analyzed. That is, if a tie is centrally positioned, it knows about the information that others possess and has low-cost access to this information, no matter where this information is located in the network. Moreover, a position bridging a structural hole between otherwise disconnected groups of people is more beneficial because it gives access to the people who circulate in different flows of information and therefore the benefits they provide to each other are rather additive (Burt 1992, 2001).

In the dissertation we analyze the relationships between two given users in the network. As tie strength is not embedded into the SNS platform, we assess the impact of underlying tie strength on the value of information users derive from their network. It is not clear whether it is rather strong or weak ties are associated with information value on SNS. On the one hand, these networks offer unique possibilities to maintain relationships and obtain resources from a broad network of weak ties, the information from whom is constantly appearing on the Newsfeed. On the other hand, as SNS support underlying relationships, users might be more interested in the information coming from their stronger ties on the network, as this information possesses more intrinsic value and is easier to process. At the same time, information value is not only determined by a single structural property of the network. For example, the number of mutual friends – the readily available information on user’s profiles – shows the relative overlap in the network of two given users. That is, the more overlapping are the networks of two users are, the more redundant information they will possess and thus will be less valuable. Therefore, we stress the necessity to differentiate between measures of network structure and explore their impact on the value of information.

2.2 Information Characteristics

Information is the valuable resource that flows between the users in a network (Figure 1). We explore the characteristics of the information flows and the impact on the value of information users derive on SNS. Relating to any piece of content that is shared by a user on the network, we differentiate between: the properties of information such as breadth and depth, contextual information, relational information about the person who shared the content, as well as social information from other users in the network. We want to understand what is the impact of these informational properties on the value of information people obtain from their networks on SNS.

Concerning the properties of information itself, we can delineate breadth and depth. Breadth is the amount and frequency of information that is exchanged on the network. Breadth has important implications for the value of information, as it directly relates to information overload (Schultz and Vandebosch 1998). That is, initially increasing the amount of information has a positive impact on information value, but after a certain threshold, the amount of benefits diminishes, and might result in information overload (Schneider 1967). On SNS, a lot of information is shared which competes for user’s attention and decid-

ing on what to focus is an important task. Therefore, identifying the strategies that users apply to process information is one of the main goals of this dissertation.

Depth rather refers to the qualitative properties, such as the understandability of information that is shared on SNS. Knowing the language of communication is a prerequisite of interpreting information, but what is more important is the shared meaning of the information. A lot of information that is exchanged on SNS is ambiguous for interpretation (Koroleva et al. 2010) and therefore understanding its context becomes important. Context hereby refers to motivations, implicit meanings or other meta-information that is embedded into it. Information might possess different meanings to different individuals, and therefore establishing shared meaning of the information is important for estimating its value (Miranda and Saunders 2003). In order to establish shared meaning, the role of contextual information, the relational as well as social information from others in the environment is assessed.

Social Context Cues

Social presence theory, the social context cues hypothesis and media richness theory discussed in section 1.3 recognize the absence of contextual cues as the critical difference between FtF and CMC (E-mail) communication. SNS, however, might challenge this proposition by providing a lot of social context cues to its users. These cues allow to process information more quickly and effectively (Dennis and Kinney 1998), as well as establish the shared meaning quicker (Miranda and Saunders 2003). Moreover, a lot of the information shared on SNS is ambiguous without understanding its context, where the role of contextual cues for interpreting this information becomes particularly acute. We differentiate between relational, contextual and social information.

Contextual Information

Contextual information is defined as all the information that surrounds the content that is shared on SNS and includes: I) type of information (status update, link, picture); ii) verbal indicators (abbreviations, lexical surrogates); iii) referrals through tagging other users or places. SNS allow users to share not only text, but attach pictures, music and videos that can provide additional cues to the recipients. These alternative types of information help to transfer information more effectively (compare the effort necessary to process pictures as opposed to text), as well as transmit a lot of tacit information – information that is difficult to put in words – critical to establish shared meaning.

At the same time, verbal indicators can also convey contextual information necessary to develop shared understanding (Burgoon and Hale 1987): lexical surrogates provide for informal communication, whereas various linguistic cues can express immediacy of communication (Walther 1992). SNS users use a lot of linguistic surrogates, such as hearts and smileys that help to transfer their emotions and intentions to other communication partners and thus enrich the context of communication. At the same time, they also use a lot of abbreviations which increase the speed of communication and establish specific norms of interaction on the platform.

Finally, referrals can call the attention of other users to the information that is shared and thus ensure that the information reaches the people to whom it provides most value or provides opportunities of an unexpected contact (Burt 2002). On SNS users are able to tag others in their post and thus either dedicate the information to them, call their attention or otherwise indicate the affiliation of others with the information. All in all, understanding the impact of the contextual information on its ability to provide for the shared meaning as well as impact information value is what we will extensively explore in the section B3.5.

Relational Information

Relational information is defined as socially revelatory information about a communication partner (Walther 1992). On SNS any information that is shared is accompanied by cues relating to the sender of information and the relationship with the receiver of information, such as: i) information on the profile, which includes but is not limited to profile picture, name or nickname, basic information, number of friends, number of mutual friends; ii) history of communication both publicly (by commenting and liking) and privately (through messages and chat) between sender and receiver which is supported by the timeline feature. This information helps to establish the context of communication and ensures a sense of presence of the person who is sharing the information (Short et al. 1976). Since the relationship between the sender and the receiver of information is not embedded in the platform, the history of communication between them can be used as a proxy to determine the strength of their relationship (Gilbert and Karahalios, 2009). Moreover, the number of mutual friends on the profile of the user might indicate the redundancy of the network as discussed in section 2.1. Therefore, understanding the role of relational information on the information value on SNS is another interesting research question which we will explore in the section C3 of the dissertation.

Social Information

As opposed to the contextual and relational information that comes from the person who is sharing the information, social information concerns the opinions of other users in the network. Social information is defined as the perceptions of others in the social environment about the information that is shared (Fulk et al. 1987), thereby tapping into the network level of analysis (cf. Figure 3). It also serves as the feedback from others on the information they receive. Although social presence theory refers to non-verbal cues such as gestures and facial expressions as social information (Short et al. 1976), we refer to social information in lieu of social influence model. The social influence model explores the impact of behavior, statements, interpretations, and cognitive assessments by others in the environment on individual perceptions about communication media (Schmitz and Fulk 1991) and confirms its impact on technology adoption and use (Kraut et al. 1998). Through feedback mechanisms provided by the platform, individuals learn from others (Bandura 1977) and adjust their behaviors accordingly (Bandura 1963).

On SNS two distinct types of social information can be distinguished: ratings and comments which serve as the means for other users to provide feedback on the information that they receive. Ratings and comments are important in that users can adjust their behavior based on them as the reinforcement learning

theory suggests (Bandura 1963). By observing different outcomes from their information sharing behaviors, users develop certain heuristics and can apply them in the future. As users tend to be influenced by others (Bandura 1977), ratings and comments from others might help them evaluate the information that is shared. Finally, in the conditions of increasing information overload, ratings and comments might help users to process information by focusing their attention.

Ratings are standardized mechanisms that allow users to evaluate their perceived value of information on a standardized scale, such as one-sided affirmations (e.g. Facebook ‘like’), binary decisions (e.g. Digg up or down), or along a continuum (Amazon’s 1-5 stars). On such SNS as Facebook mainly one-sided affirmations are used, as providers fear propagation of negative feedback. Comments are open-ended mechanisms that allow individuals to register their more elaborate opinions on certain digital content. Although these two types of feedback are sequential, ratings from other users are akin to non-verbal responses (such as thumbs up or down) and therefore might partially play the role of concurrent feedback. Especially the one-sided ratings (likes) signal to the receiver that there is a certain number of users who have understood and agree with the information shared. Ratings can thus provide instant impressions of the information and promote the presence of other people who interact with the content on the platform. On the other hand, the more elaborate comments are rather used to clarify the message, elaborately agree with the content, complete the statement or express a controversial opinion – the goals akin with the definition of sequential feedback (Daft and Lengel 1986). We will explore the impact of these two types of feedback more elaborately in the section B3.4 of this dissertation.

2.3 Experience with SNS

Although evaluations of communication media based on their richness (cf. section 1.3) works well in theory, empirical tests have produced inconsistent findings, especially in case of new media, such as electronic and voice mail (Trevino et al. 1990, Webster and Trevino 1995). Channel Expansion theory explains these inconsistencies using the dimension of time: that is, with increasing experience with the medium itself, the person with whom one is communicating as well as with the context of communication, the capacities of the channel for rich communication will increase (Carlson and Zmud 1999). As users communicate more through the medium, they gain experience, develop the shared meaning and therefore subsequent communication tends to be more effective, thus increasing the perceptions of usefulness of the medium for communication. Especially the experience of communication with the channel and the communication partner significantly impacts media richness perceptions (Carlson and Zmud 1999).

When studying SNS, control for the experience of users with the medium. As the functionality of SNS expands and users observe the behavior of others on the network (as discussed in section 2.2), they understand which information is best suitable for sharing and how to best share that information and as a result perceive SNS as useful media for communication. On SNS, users typically broadcast information to an entire network of connections simultaneously, so it becomes possible to maintain connections through public communication. However, it remains unclear how this trait might influence the develop-

ment of the relationship and shared usage of the platform to support channel expansion. On the one hand, increased public sharing of information may contribute to the maintenance of the relationship with each participant of communication. On the other hand, as too much information is exchanged in a short amount of time (Shultz and Vandebosch 1998) and the user does not share meaning with all other participants of information exchange (Miranda and Saunders 2003), it might be difficult for the user to develop shared usage that expands the channel.

Table 1 **Typology of SNS Use**

SNS use	Way	General platform use
		Communication with friends
	Frequency	Very frequently – very rarely
		Once a day, once a week, once a month
	Duration	Running in the background – 2 hours a day – 1 hour a day – 30 min a day – 10 min a day – less than once a day
	Type ¹	Active Participation (public)
		Passive Following
		Network Construction
		Social Browsing
		Private Communication
	Direction	Use oneself
		Use by others

As users develop experience communicating with specific others, they develop a knowledge base about them. On the one hand, experience of communication allows to better understand the needs of the person, the knowledge and the abilities thus contributing to transactive memory about that person (Borgatti et al. 2009). At the same time, in this process communication style and cues that this person uses are learned, thus contributing to the shared meaning of information. Hereby the relational and contextual cues described in section 2.2 contribute to the speed with which this meaning is developed. Channel expansion theory therefore suggests that people will extract more valuable information from those they know better and have more experience in communication with (Carlson and Zmud 1999). At the same time, SNS are especially useful in supporting the weak ties (Donath and boyd 2004). Reflecting on the discussion in section 2.1, we would like to explore the impact of experience of communication with the person on tie strength and subsequently, on the value of information that is exchanged on SNS.

¹ - these types of use emerged based on the findings of the study presented in section C

Recognizing the importance of the experience factor for user perceptions regarding SNS, we control for it in different ways in the dissertation, depicted in Table 1. Following Carlson and Zmud (1999) we distinguish between the intensity of general SNS use and the experience in communication with other users on the network. On the one hand, we control for the general frequency and duration of SNS use (cf. section B3.4). On the other hand, we extensively explore the impact of the intensity of communication with a specific user on the information value from that user in section B3.5. We also explore how communication intensity on SNS relates to the development of the underlying tie strength between users in section B4. Moreover, not every type of use of SNS use will result in the same benefits for its users. Therefore in section D4.2 we identify the different types of use and in section B4.4 explore the impact of these types of use on social capital benefits that accrue to users due to their relationships with others. Finally, we can differentiate between the direction of use: either the usage of the system by the user oneself or by other users of the system. As such, posting oneself may be positively related to information value (discussed in section C3.2), whereas users might be annoyed by others posting similar information (elaborated in section B3.5). We assume that these different types of SNS use might have different impact on how information is evaluated by users.

3 Theoretical Framework of the Dissertation

3.1 Aligning the Research Questions

Since their launch, researchers in various disciplines have been studying various questions surrounding the emerging phenomenon of SNS. In IS, a significant body of literature is dedicated towards understanding the motivations behind SNS use (e.g. Joinson 2008, Morris et al. 2010), the impact of intensity of SNS use on social capital (Ellison et al. 2007, 2011, Burke et al. 2010, Tufekci 2008, Valenzuela et al. 2009, Vitak et al. 2011), privacy concerns (e.g. Krasnova et al. 2009b, Krasnova et al. 2010b), impact of profile features (e.g. Tom Tong et al. 2008), sentiment of interactions (Schöndienst and Dang-Xuan 2012). In social sciences, a recent overview study by Wilson et al. (2012) identifies 410 relevant articles that explore various research questions regarding the new phenomenon of SNS. The authors classify the research questions these studies address into those relating to: i) characteristics of users; ii) motivations for use; iii) self-presentation strategies; iv) relationship development; iv) self-disclosure and privacy.

However, these studies usually explore just one question connected with SNS without assigning it to the overall framework. What most of them fail is to address such questions as: Why is it important to study SNS? How do these environments differ from other forms of CMC-communication? How do they relate to the real-world behavior of users and impact their lives? Addressing these important questions, Kane et al. (2012) propose a framework which structures all research questions relating to SNS along two dimensions: source of social capital and locus of agency. The source of social capital is important in the sense that it allows to differentiate whether the benefits of a network stem from the resources that flow in the network (i.e. information) or through properties of the network structure (Nahapiet and Ghoshal 1998).

The locus of agency, on the other hand, allows to differentiate whether benefits are rather due to the functionality of the medium or the users.

In order to structure the research questions that we address in this dissertation, we adopt and extend this framework. First of all, we explicitly differentiate between dynamics vs. outcomes (Kane et al. 2012). The former is rather concerned with how networks and information forms, whereas the latter with outcomes to which these properties lead. Moreover, considering that these environments involve not only the individual in question, but also connections to and interactions with other individuals on the platform, which impact behavior of the user in question, we add social environment to the locus of control dimension. Therefore we can position each research question we address in a three-dimensional space with the following axes: a) source of social capital (content vs. network); b) the dynamics (sources vs. benefits); and c) locus of control (user vs. platform vs. social environment). The corresponding research questions that are addressed by the publications comprising this dissertation are summarized in Table 2.

The motivation behind differentiating between the sources of social capital - content vs. network – is reflected in the functionality of SNS that allows to support these two types of ties (cf. Figure 1). On the one hand, as a result of connections to each other, individuals form networks of relationships, the properties of which are discussed in section 2.1. Depending on the configuration and properties of the network, different benefits of social capital can be attained. For example, a network rich in structural holes might result in less redundant informational benefits and the access to the more diverse resources of others. On the other hand, SNS provide for different types of interactions, during which vast amount of information is exchanged, which can trigger subsequent interactions and thus promote relationship development or other benefits of social capital. The differentiation between network and information is most vivid in the dissertation, as we first study the impact of information characteristics (depth, breadth, context), and then the impact of network properties (tie strength, network overlap) on information value. However, by interacting between the two we are also able to uncover quite interesting dynamics as well.

Differentiating between the dynamics of sources vs. benefits allows us to capture the following causal relationship: usage of the medium translates into accumulation of the information sources and formation of a network structure, which under favorable conditions may lead to the benefits of social capital. In fact, social capital it is defined not only as the tangible benefits that accrue to its users, but also as the sources in which these benefits are contained (Resnick 2001, Nahapiet and Ghoshal 1998). For example, a diversified network structure rather results in bridging benefits of social capital, whereas a more closed network usually leads to social support (Ellison et al. 2007). Therefore, in the dissertation we not only address the questions of how the users form their networks, but also what impact do the resulting networks and their properties have on information value. Moreover, we differentiate between information as a source of transactive knowledge (such as accumulation of knowledge who knows what and possesses which resources) and as a benefit (activating that knowledge to get access to the resources of others or broadening ones outlook as a result of learning new information).

Distinguishing the different loci allows us to determine to which extent the sources and the benefits that are contained in the information and the network are determined by the user, the platform or the social environment. Users characteristics include the frequency, duration and mode of SNS use. For example, some users might prefer to actively contribute content quite frequently, whereas others prefer passive following of what others post. How do these patterns of user behavior relate to information value?

Table 2 **Aligning the Research Questions**

		User	Platform	Social Environment
Information	Sources	B2. ² What is the impact of the shared meaning on the depth of information?	B3. How can providers optimize information presentation for users? (filtering, ranking)	B2. What is the impact of posting frequency on the breadth of information?
	Benefits	B2. What is the impact of information characteristics (e.g. breadth, depth) on information value? D1. What is the impact of shared information on social capital benefits?	B2. What is the impact of information characteristics provided by the platform (e.g. post type) on information value?	B1. What is the impact of social information on information value?
Network	Sources	C1. How do users construct their networks? C1. Why do people add users of different tie strength?	C1. What is the impact of privacy and control settings on network construction decisions? B3. How can tie strength be best predicted using available network data?	C1. What impact does social pressure have on network construction behavior? C1. What is the impact of social norm on the desire to add people of different tie strength?
	Benefits	B1. How does tie strength between users impact information value? D1. How does network structure impact social capital benefits?	C2. How does network overlap impact information value?	B1. What is the impact of the interaction of social information and tie strength on information value?

² the numbers indicate the corresponding papers listed in Table 3

The social influence (Schmitz and Fulk 1991) as well as the observational learning theories (Bandura 1977), suggest that people's opinions impacted by their social environment. As users interact with others on SNS or observe how others interact, they adopt certain modes of behavior that they apply in the future. Therefore, which role do peer pressure and social norms have on the network construction behavior of users? Moreover, the theory of reinforcement learning postulates (Bandura and McDonald 1963) that people adjust their behavior according to the feedback they receive from others. As such, what is the impact of the feedback provided by others on the value of information users obtain?

We should not underestimate the impact of platform functionality on the information and network sources as well as the benefits users obtain on SNS. These include the way the content can be shared (length of post, supported post types), features that allow users to interact with the content (ratings and comments), the types of ties that are supported, the functionality to limit accessibility of information to certain types of ties (through privacy settings), algorithms that filter the information. In this respect, what is the impact of information characteristics provided by the platform (such as post type) on information value? Moreover, what is the impact of the functional controls users have at their disposal on their decision to integrate someone into their network? Finally, how can network providers optimize information presentation to the users so that to maximize the value they obtain from the content that is shared on the network?

We have to note, however, that the impact of the platform and users, as well as user and social environment can not be determined unambiguously. The very concept of SNS implies that users form the ties with others, so that the value that is created in this process can not be unambiguously attributed either to the platform which enabled the connection or the users whose connection is largely determined by the underlying relationship. At the same time, ratings and comments are provided by the platform, but are used by the social environment to provide feedback on the content that is shared. Therefore, the main questions we address in this dissertation are: What is the impact of the social information on information value? What is the impact of tie strength on information value? And finally, what is the impact of the social information, differentiated by the different levels of tie strength? These questions are addressed in the parts of the dissertation that follow.

3.2 The Generic Model

As depicted in the Figure 4, the process of social capital formation on SNS on the macro-level can be summarized as follows: the functionality offered by the platform combined with the patterns of use that users develop on SNS encourage the accumulation of information and network sources, which under favorable conditions can translate into benefits, be it either valuable information or social capital. In the chapters of the dissertation, we differentiate between the main sources of social capital benefits, namely network structure and information characteristics in their impact on the benefits of social capital. Moreover, we explore the impact of user characteristics reflected in the experience with the medium in general and other people in the network in particular as well as social information on informational and other benefits, whereas implicitly considering the underlying platform functionality.

On a micro-level, the model presented in Figure 4 holds when user is evaluating any piece of information that is encountered on the network. As such, this information is accompanied by several informational properties, such as: the breadth, the depth, and contextual features. Additionally, the person who is sharing this information is assessed, specifically the underlying relationship and the overlap in the network. Social information from other users in the network is taken into consideration, as it provides additional cues to estimate the value of information. Thus, taking into account the information characteristics, the network properties and the social environment the value of information can be assessed. In the background, user characteristics, such as the experience of users with the medium or in communication with the person who is sharing the information might accelerate or constrain the assessment of information. At the same time the underlying network functionality determines breadth and depth of information, as well as allows to visualize the network.

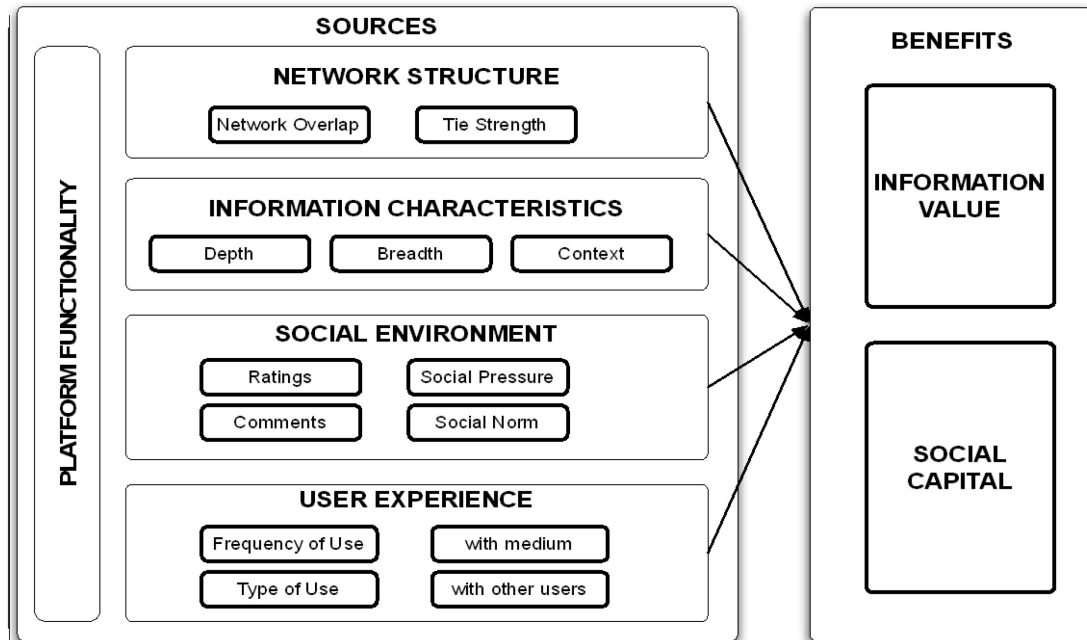


Figure 4 The Generic Framework

The generic model presented in Figure 4 captures most of the models explored in the dissertation in a series of peer reviewed publications presented in Table 3. As the model is very holistic, we explore parts of it in the corresponding sections of the dissertation. In *section B* of the dissertation we mainly explore the content that is exchanged on the platform from both perspectives: on the one hand, which content the users focus on, and on the other hand, which content is enabled to the user by the platform. What concerns the user, in study B2 (cf. Table 3) we explore the impact of information characteristics, such as the breadth and depth of information on the information value that users obtain from their network. In study B1 (cf. Table 3) we explore the impact of social information (ratings and comments) on the value of

information on SNS. Specifically, we want to explore if social information has a different impact, depending on the underlying tie strength with the person who is sharing that information. In both studies we control for the experience with the medium (study B1) and experience of communication with the person who is sharing the information (study B2). What concerns the platform, in study B3 (cf. Table 3) we explore the ways of improving information presentation to the user to decrease information overload and increase the value of information. The questions we address in this part of the dissertation are rather located in the information as a source of social capital dimension of the Table 2.

Table 3 **Peer-reviewed Publications included in the Dissertation**

Part	Peer-reviewed Publications
B. Information Processing and Information Value	B0. Koroleva,K., Krasnova, H. and Günther, O. 2010. ‘Stop Spamming Me!’ – Exploring Information Overload on Facebook <i>Proceedings of the Americas Conference on Information Systems (AMCIS 2010)</i> , AIS Electronic Library, Paper 447.
	B1. Koroleva,K., Stimac, V., Krasnova, H. and Kunze, D. 2011. ‘I like it because I’(m) like you’ – Measuring User Attitudes towards Information on Facebook. <i>Proceedings of the International Conference on Information Systems (ICIS 2011)</i> , AIS Electronic Library, Paper 26.
	B2. Koroleva,K., Krasnova, H. and Günther, O. 2011. Cognition or Affect? – Exploring Information Processing on Facebook. A.Datta, S.Shulman, B.Zheng, L.Shou-De, S.Aixin, and L.Ee-Peng, eds. <i>Social Informatics, Lecture Notes in Computer Science</i> , Volume 6984, Springer Berlin/Heidelberg. 171-183.
	B3. Koroleva, K. and Bolufe-Röhler, A. 2012. Reducing Information Overload: Design and Evaluation of Filtering & Ranking Algorithms for Social Network Sites. <i>Proceedings of the European Conference on Information Systems</i> , paper 12.
C. Network Construction and Network Structure	C1. Krasnova, H., Koroleva, K., and Veltri, N. 2010. Investigation of the Network Construction Behavior on Social Networking Sites. <i>Proceedings of the International Conference on Information Systems (ICIS 2010)</i> , AIS Electronic Library, Paper 182.
	C2. Koroleva, K. and Stimac, V. 2012. Why information from lovers is more valuable than from close friends on social network sites? Submitted to the International Conference on Information Systems (ICIS 2012).
D. Process of Social Capital Formation	D1. Koroleva, K., Krasnova, H., Veltri, N. and Günther, O. 2011. It’s all about networking! Empirical Investigation of Social Capital Formation on Social Network Sites. <i>Proceedings of the International Conference on Information Systems (ICIS 2011)</i> , AIS Electronic Library, Paper 24. Best Paper Award.

The *part C* of the dissertation is devoted to studying the networks of users, their evolving structure and its impact on information value. Here we can clearly recognize the distinction into the sources vs. outcomes: on the one hand, dynamic theories that explore how networks form, whereas outcome theories that study the benefits that users obtain. In study C1 (cf. Table 3) we explore how users construct their networks and which factors motivate them to do so. The assessment of benefits and costs of adding people to the network might differ based on the strength of the relationship with the person. Then, in study C2 (cf. Table 3) we assess the networks that users construct, i.e. their properties on the value of information that users obtain from their network. We stress the necessity to differentiate between two measures of network structure: tie strength and network overlap in their impact on information value. Tie strength might be associated with information value, however network overlap might signal the redundancy of the network. The questions we address in this part of the dissertation are located in the network as a source of social capital dimension of the Table 2.

In *part D* of the dissertation we explore the impact of shared information and network structure on the social capital benefits users obtain from their network. We especially address the source-outcome relationship by conceptualizing and empirically testing the process of social capital formation in study D1 (cf. Table 3). Specifically, we show how the frequency of different types of SNS use leads to accumulation of information and formation of the network and how these sources, in turn, impact the attainment of the benefits of social capital. Thus, we view information that users obtain from their network as a source that may generate other benefits or as a benefit in itself. If we view it as a source, it is the main product of user interactions that may encourage interactions in the future and thus improve the relationship and provide better possibilities to obtain their resources when needed. If we view it as a benefit, it rather refers to such more tangible benefits as horizon broadening (Williams 2006). As such, the questions we address in this part of the dissertation are located in the lower rows in both information and network parts of the Table 2.

4 Methodological Introduction

IS research can be assigned to one of the following streams: i) design science research on the design of IT-based artifacts; (ii) behavioral research on understanding issues like user acceptance or other impacts of IT; (iii) economic research on the value of IS; (iv) strategic and organizational on the management and impacts of IT in organizations (Baskerville et al. 2011). The goal of this dissertation is the evaluation of the perceptions of users about the value of SNS as the medium for information exchange and maintenance of relationships with friends. In order to measure this value, we need to collect behavioral responses from participants about their subjective experiences with using SNS, such as perceptions of value, underlying tie strength, and other concepts that we explore. Therefore, the studies presented in this dissertation mainly focus on behavioral research paradigms and explore the usage patterns of SNS as well as the impact these networks have on the benefits users gain. However, other research streams can be traced in this dissertation as well. For example, in order to collect data, we design and program applications that allow to collect the data in real time. The applications allow us to collect a lot of objective data about user behavior on the network and combine them with subjective evaluations of users. In fact, Hevner (2004)

stresses the value that is achieved by combining behavioral research with design science to address fundamental problems posed in IS. The overview of the methods used in the dissertation is presented in Table 4.

Table 4 **Methodological Approaches of the Dissertation**

	Data collection	Empirical method	Methodology	Robustness Check
B0	Participant Observation	Qualitative	Grounded Theory	Literature
B1	Facebook Application I	Quantitative	Ordered probit	Panel GLS, OLS
B2	Facebook Application I	Quantitative	SEM	Regression GLS
B3	Facebook Application I	Quantitative	Neural Networks	Other Algorithms
C1	Participant observation	Qualitative	Grounded Theory	Literature
	Survey	Quantitative	SEM	none
C2	Facebook Application II	Quantitative	Random Effects Logit	Fixed Effects Logit
D	Observations, interviews	Qualitative	Grounded Theory	Literature
	Survey	Quantitative	SEM	none

Behavioral Research

In most of the studies we present we use methodological triangulation. First of all, we use triangulation between qualitative and quantitative methodologies. That is, we use qualitative methodologies at the exploratory stage to generate the conceptual models, and then use different quantitative methodologies to empirically test them. The qualitative methodology we use is Grounded Theory – which was mainly used in social and medical sciences to study complex concepts, such as pain (Strauss and Corbin 1998). The advantage of Grounded Theory (GT) is that it is rooted in the iterative comparative analysis during which data and emerging theory are routinely compared for validity (Seidel and Recker 2009; Strauss and Corbin 1998). This approach helps researchers to analyze available data systematically and uncover the underlying relationships. We find that it can be best applied to study such complex and subjective concepts as information overload or social capital. However, we do not only view qualitative models as exploratory, but also sometimes use them in a confirmatory way, that is to explain the relationships we find in our empirical models that could not be explained by the existing theory.

Even though GT is in most cases exclusively based on the qualitative data (e.g. Orlikowski 1993; Pace 2004), Glaser (1992) is calling for more use of quantitative evidence to support research propositions. While the main aim of the GT approach is to build theory (e.g. expressed in a set of propositions), other methods can be used to verify it (Pace 2004). We therefore employ either the Structural Equation Modeling or regression analyses to quantitatively test a set of relationships as suggested by the qualitative data. Regression Analysis has the advantage that it can be tailored to the usage on the dependent variable of a specific type (ordinal, binary, continuous). Moreover, regression analyses do not require operationalization of latent constructs and allow to measure emerging concepts with just one indicator. Finally, we can

control for the respondent-specific effects using panel regression methodologies and thus do not have to explicitly control for such variables as gender, age, the mood of the user on the day of answering the survey, etc.

SEM has the advantage that it is best suited to test the exploratory models – the ones that we generate based on the qualitative data. At the same time SEM has the advantage that it can be used with non-normally distributed variables, which is the case for many of the variables we collect in surveys. Moreover, SEM is best suited to test such latent constructs as attitudes and evaluations of users, which are mainly the focus of our analysis. By measuring user perceptions by a latent construct we are better able to capture the full experience of users with the medium, and not just single facets of it.

Furthermore we use methodological triangulation when we test our empirical models. Most of the models are tested via several different methodologies to ensure that our findings are robust and the identified patterns are present in the data, rather than driven by the employed methodology (cf. Table 4). For the models that are derived based on the qualitative data, we confirm the findings by comparing them with the existing literature. If a regression model is tested, it is always verified with an alternative: for example, if a random-effects specification is used, it is verified by a fixed-effects one. The use of fixed effects offers the advantage of robustness in the presence of correlation between the set of explanatory variables and the respondent-specific effect. Random effects, on the other hand, is useful if the unobserved respondent-specific effect is correlated with other omitted effects that are captured by the error term. If we want to delineate the impact of two variables with an opposite impact on the dependent variable, we test the regression by excluding each of them and comparing the coefficients. If they get closer to 0, we are able to show the effect of the omitted variable bias, and thus inversely argue for the necessity to include this variable in the analysis. Moreover, in one of the studies we verify the findings of SEM by a panel regression methodology and thus are able to combine both methods.

Elements of Design Science Research

We also use the elements of design science in the dissertation. This is by far determined by the nature of our research question: to determine which information users find useful on SNS. As each evaluation is specific to the piece of information that is shared on the network, we can not collect the data with the usual survey. We could consider conducting participant observations, but this would cost much more effort and we could not ensure the objectivity of such a methodology. From a research standpoint, SNSs and other social media platforms provide substantial benefits in terms of the sheer volume of data available about user activity (Kane and Fichman 2009; Lazer et al. 2009). Moreover, this data offers us the ability to easily trace their real behavior on the network, which the users are not able to assess objectively on their own. However, the raw data that is saved by the platform might not provide us with the necessary insights. At the same time, however, some information critical for estimation of information value can not be extracted from the social network. One example of such information is the underlying tie strength of the relationship between users, which is not embedded into the platform. What we need is the combination of the subjective user evaluations of the information with the objective features provided by the platform. Facebook offers an API and allows third-parties to develop applications that with the user's per-

mission access the information. Thus, if we design such an application, we are able to access the information that is on the user's Newsfeed in real time and ask the users to evaluate this information, whereby collecting the data about the additional factors we want to explore. Therefore, designing an application will allow us to combine the subjective evaluations of users what concerns such latent constructs as their attitudes, with more objective measures of their behavior.

Another design artifact we develop, using the categorization proposed by March and Smith (1995), is a method to present information to the user on the Newsfeed. Based on the empirical findings of studies presented in the sections B3.4 and B3.5 we design and evaluate several ranking and filtering algorithms for SNS in the section B4. We use neural network algorithms to show that by already including the social context data into account we can increase the accuracy of information prediction. A neural network algorithm uses one part of the dataset to learn about the relationships between the input and output variables, develops certain rules and then applies these rules to the rest of the data (and based on this estimates an accuracy metric). The advantage of the algorithm we design is that we include only those input factors which have significant impact on the users' evaluations.

B Information Characteristics and Information Value

1 Introduction

The Social Network Site (SNS) Facebook is the largest database of social information, increasing at a rate of 30 billion pieces of shared content per month (Facebook 2011a). The constant information updates in the Newsfeed dynamically deliver hands-on information on the actions of friends ensuring that a user always has something new upon login - a reason to come back and stay loyal: “But if I did not have all this, I would log-in here, and then what?” (Interview Quotation (Q)). Users rely on the information exchanged through these networks for news (Glynn et al., 2012), purchase decisions and other personal issues (Lampe et al. 2012), relationship development with friends (Köbler et al. 2010) and even the benefits of social capital (Ellison et al. 2007).

However, due to the increasing amount and varied quality of information that is exchanged on the network, this active sharing is bounded by the problem of *information overload* - a phenomenon referring to the emotional state of dissatisfaction and inability to cope with incoming information (Eppler and Mengis 2004). Taken that attention users are ready to invest in SNS activities is limited, perceived information overload can lead to emotional distress and dissatisfaction (Eppler and Mengis 2004), confusion, stress, anxiety (Schick et al. 1990), as well as diminishing decision quality (Chen et al., 2009a). On SNS, users feel dissatisfied and thus may reduce their activity (Koroleva et al. 2010), which is detrimental for the longevity of SNS providers. Such developments are highly undesirable as financial and social success of SNSs is largely dependent on user activity rates (Krasnova et al. 2009a). Thus, information overload represents an acute phenomenon to be studied on SNS.

Recognizing this problem, Facebook introduces information filtering. Scattered insights suggest that on Facebook algorithms prefer posts which have received more feedback, as well as from those friends with whom users previously interacted (Kincaid 2010). However, the algorithm does not take into account other seemingly important factors, such as as length of post or friend posting frequency which might cause information overload on SNS (Koroleva et al. 2010). Moreover, preferring information from those with whom the user interacts often online is not optimal. First, users may prefer other means to communicate with their close friends (Vitak et al. 2011). Second, the value of recommender systems lies in discovering new content outside of the user’s usual social circle (Chen et al. 2010). Notwithstanding the filtering, SNS users are largely dissatisfied with the information presented to them (Tonkelowitz 2011) and therefore more insights are required on how to design such systems for SNS.

Being overloaded with information, users have to apply certain strategies to process and evaluate the information that is presented to them. Thus not only the system determines the information that is being exchanged, but also the user herself, reflecting the discussion in section A3.1. As users are limited in their cognitive capacities and motivation, it becomes critical to understand which information users focus on. Due to the absence of systematic research investigating the dynamics behind user perceptions towards

information on SNS, in the first part of the dissertation we aim to empirically investigate which information users like and find useful on SNS. Specifically, we aim to identify what characteristics of information and the network have impact on the affective and instrumental information value on SNS. We thus explore how information forms on SNS and which impact it has on the value. At the same time, in the next step, we analyze how is the information presented to users by the platform.

Against this background, our aim is to first identify when information overload occurs on Facebook and what are its main sources and consequences in a qualitative study. In the second step, we conduct several empirical studies where we determine the impact of social information and contextual information on the value of information exchanged in these networks. Hereby we also control for network structure and the experience of users with the medium. Finally, based on the identified factors, we design and evaluate a Neural Network algorithm which filters and ranks the information for the user. In this way we combine the behavioral approach with the design science approach in IS.

2 Qualitative Study

2.1 Theoretical Background

Information Overload hypothesis states that information processing performance of an individual correlates positively with the amount of received information up to a threshold point, after which rising information leads to a rapid decline in processing ability and eventually results in overload (Miller, 1956). This phenomenon is also known as an *inverted u-curve* of information processing (e.g. Eppler and Mengis 2004), supported by empirical evidence in numerous studies (e.g. Sicilia and Ruiz 2010). Information overload takes place when the information processing requirements (or information supply) exceed the information processing capacity of an individual (or information demand) (Eppler and Mengis 2004). However, processing abilities differ from individual to individual, making it impossible to estimate a universal threshold level of information load (Chen et al. 2009a). Thus it becomes important to recognize the internal mechanisms by which people identify relevant information (McGuire 1976). Qualitative characteristics of information, such as novelty, ambiguity, uncertainty, intensity and complexity, generally signal relevance of information (Schneider 1987).

Consequences of information overload include confusion, inability to set priorities and recall previous information (Schick et al. 1990), as well as dysfunctional effects in form of stress and anxiety (Eppler and Mengis 2004). In e-commerce, authors repeatedly find evidence for diminishing decision quality when consumers are faced with superfluous information to be processed (e.g. Chen et al. 2009a). However, research into specific causes and consequences of information overload still remains limited (Davis and Ganeshan 2009). In particular, the concept of information overload is extremely underexplored in social media, including SNSs. This is surprising as communication overload occurring in online communities is found to impact group communication dynamics by dissipating the attention of users away from complex messages (Jones et al. 2004). On Facebook, Boyd (2008) identifies the concept of information invasion -

the inability of users to process all incoming information due to limitations of time and cognitive ability resulting in withdrawal.

Against this background, we aim to uncover the dynamics behind subjective attitude towards quantity and quality of information on the Newsfeed on Facebook. Multiple studies routinely confirm enjoyment as major SNSs gratification and reason for use (e.g. Krasnova et al. 2009a) with shared and received information as its main source (Chen et al. 2000). Addressing the problem of information overload on SNS is of paramount importance as growing quantity and increasingly poor quality of information on the Newsfeed may have serious consequences. In this respect, in this part we aim to find an answer to the following research question: *When does information overload occur on Facebook? What are its main sources and possible consequences?*

2.2 Methodological Approach

We use grounded theory in order to explore information overload on Facebook in an inductive manner (Strauss and Corbin, 1998). We choose grounded theory due to its ability to analyze qualitative data systematically, uncover the underlying relationships and generate a theory based on them. We justify our choice of methodology further by the absence of systematic research on information overload in the context of SNS, as well as due to the general practice of investigating information overload using qualitative analysis of surveys and interviews (Davis and Ganeshan 2009). We pursue the ‘Straussian’ line of grounded theory, which requires absence of an a-priori theory and emphasizes the usage of a paradigm for axial coding (Matavire and Brown 2008).

Data analysis was done on the basis of 12 semi-structured in-depth interviews of 30-45 minutes with Facebook users (all students aged 20-25; 6 male/6 female). The interviews included elements of an observation, as users were asked to log-in to their accounts and perform usual actions whereby the interviewer was asking precision questions in order to understand the reasoning behind them. Observation of real behavior, although constrained by the presence of the interviewer, allowed us to obtain deeper insights as it helped to free the respondents from the necessity to spend their cognitive resources on recall. The interviews were flexible in nature and did not specifically focus on the Newsfeed, but tried to uncover all facets of a usual Facebook experience. First, 8 interviews were conducted, during which the problem of information overload was identified. In order to deepen the initial insights, 4 follow-up interviews with focus on the Newsfeed were carried out until theoretical saturation was achieved.

All interviews were recorded, transcribed and subsequently analyzed with software tool atals.ti. On the first stage of analysis - open coding - categories and properties were identified by looking for patterns in the data in the process of constant comparison (Strauss and Corbin 1998). In total, 78 categories were identified each possessing at least one property and respective dimensions. To illustrate the process of open coding consider the following example: *“The person that irritates me here most (category: affective attitude, property: annoyance, dimension: high) is my cousin's boyfriend (category: level of relationship, property: family members, dimension: cousin). He always puts these pictures of him in these poses: here I*

am with my guitar, here I am in this pose, and here is our concert... (category: amount of information, properties: frequency and detail, dimension: high)” (Q).

The next stage of analysis - axial coding - aimed to group categories into families and uncover the relationships between resulting categories and subcategories. The coding paradigm by Strauss and Corbin (1998) - including the phenomenon, its causal and intervening conditions, action and interaction strategies, and consequences - served as a milestone for the emerging conceptual framework. Most of the categories identified during open coding were included in the framework, however some have been omitted due to their low relevance to the phenomenon. The result of analysis - the conceptual model - helps to uncover the context in which information overload occurs on SNSs.

2.3 Conceptual Model

Our data reveals that users increasingly experience information overload on the Newsfeed: *“Usually in five of these I just have one real and the others are ads or spam”* (Q). Based on extensive data analysis we formulate a conceptual model of information overload depicted in figure 1, which differentiates between: the characteristics of information and the network as *causes* of information overload; the main *phenomenon* arising from different dimensions of attitude towards information on the Newsfeed; *actions and strategies* differing in their complexity and activity level; a set of *intervening* and *driving* conditions; and *consequences* of information overload, which can have recurring impact on the causes. The model extends the framework of information overload by Eppler and Mengis (2004) in that it clearly differentiates between attitudes, strategies and outcomes and explores the relationships between them.

Phenomenon: Information Overload

In this study we uncover subjective attitudes of users towards quality and quantity of information on the Newsfeed. Psychology literature differentiates between cognitive, affective and conative dimensions of attitude. Cognitive dimension refers to evaluations of the object itself, affective describes the feelings towards the object, and conative expresses a behavioral intention (Ajzen 2005). We recognize that information overload occurs when the ability of users to select relevant information is inhibited because of the high amount and low value of information on the Newsfeed.

Cognitive attitude can be identified by the evaluative statements about the information on the Newsfeed. Referring to quantity, users often feel overloaded with information: *“This is just too much”* (Q). Referring to quality, respondents mention such evaluative pairs as: ‘useless – useful’, ‘boring – interesting’, ‘irrelevant – important’, ‘valuable – worthless’. Users are ready to invest only a certain amount of time and effort into information processing, and perceive overload if they cannot find their information timely and accordingly: *“It takes so much effort to pick out the information I am curious about, in between this and this”* (Q).

Affective attitude can be recognized by the expressions of admiration or frustration about the Newsfeed, revealed in such evaluative pairs as: ‘calm – irritated’, ‘happy – annoyed’, ‘like – dislike’, with most

expressions having a negative connotation: “*This is really annoying to have a whole page filled with this...*” (Q).

Conative attitude refers to expressions of behavioral intentions with respect to the information on the Newsfeed, such as: “*I don’t want to know*”, “*I don’t want to spend my time*”, “*I should delete this*” (Q). Attitudes operate through different, but mutually influential psychological mechanisms: values shape the cognitive attitude, which in turn influences the other two dimensions (Yang and Yoo 2004). Consider the following process of information overload formation: “*This Newsfeed is somehow bad (affective), because these things that people do fill up all the news, and the others that are really interesting, just go down (cognitive), so I would like to filter it more (conative)*” (Q).

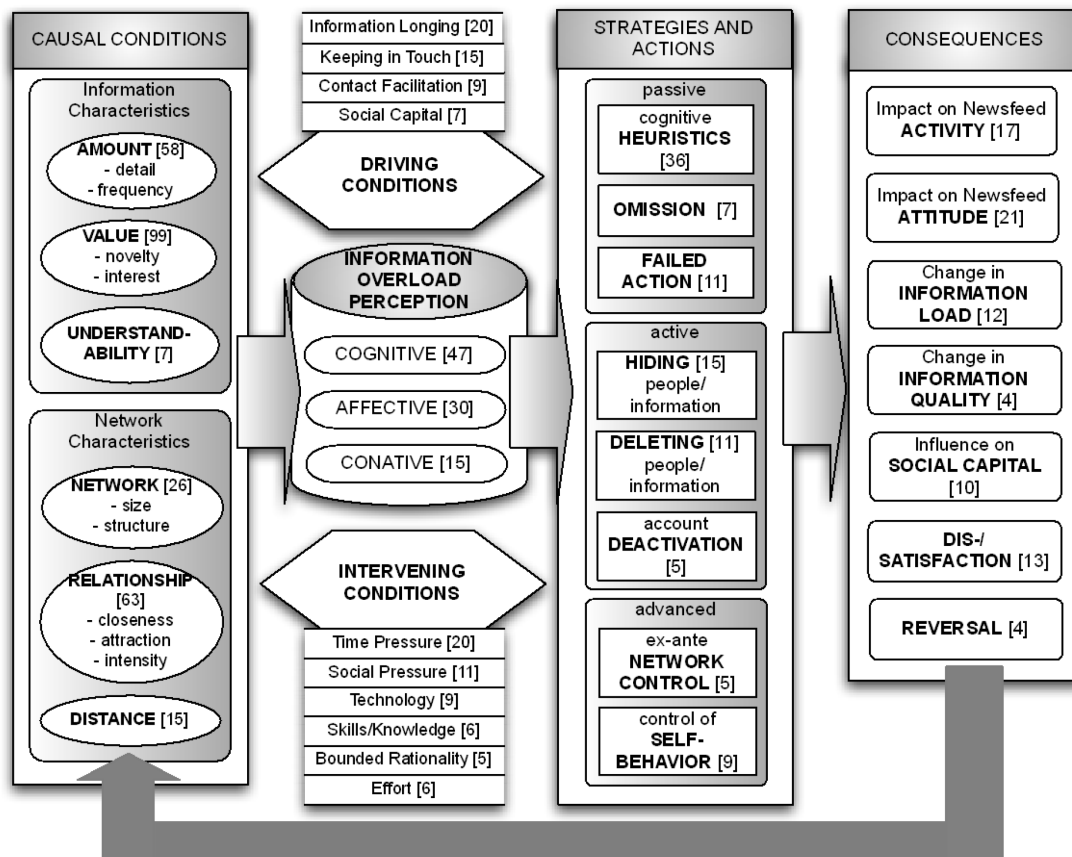


Figure 5 Conceptual Model of Information Overload on SNS³

Causal Conditions

Causal conditions are conditions that lead to the development of information overload (Strauss and Corbin 1998). In our model we distinguish between information characteristics and network characteristics as major sources of information overload. We find that among information characteristics amount, value and

³ - In the figure the numbers in brackets indicate the number of times the respective concept was mentioned by participants thus hinting at the relative importance of each concept

comprehensibility of information under certain circumstances can lead to perceptions of information overload. Summary of possible information-based cases of information overload is presented in Table 5 showing distribution of quotations and examples for each category. We can clearly distinguish two dimensions– breadth and depth of information which we discussed in section A2.2. For example, the categories amount and frequency clearly reflect the depth of information, whereas detail, comprehensibility and novelty – depth of the information.

Users are looking for immediate gratification by information best tailored to their individual perception of value and are dissatisfied when this need is not met. Information is appreciated if it has a valuable component in it, such as pictures, status updates, commented posts. However, value is highly individual-specific. Novelty and interest are major determinants of value, as recognized in previous studies (Eppler and Mengis 2004; Schneider 1967). Generally users look for new and important information from a wider circle of friends, engage in stalking on ‘interesting’ people or view content that matches their tastes.

Table 5 Information Characteristics as Sources of Information Overload

Amount of Information [14]		Value of Information [28]	
<i>“You get hundred Newsfeeds every couple of hours that you don't really want to read at all”</i>		<i>“She took this test and she found out that she is a little sheep on a green field... What is this? It is not even the real information, this is absolutely nothing...”</i>	
Detail [17]	Frequency [27]	Novelty [47]	Interest [24]
<i>“Who is attending where, which party... Three people are now friends with five other people... This is too much for me”</i>	<i>“Every second message is from Sam and most of them are not useful to me”</i>	<i>“This is boring, he was at the Beatles concert, and I know it”</i>	<i>“James posts a lot of videos, and I watched them but I did not find them funny.”</i>
Comprehensibility [7]			
<i>“And I don't know what she is talking about, 'I feel like I never left', left what, who, when?”</i>			

Perceptions of overload depend on the quantitative characteristics of the network and quality of relationships in it. Usually, not only the size and structure of one’s network has an impact on information overload, but also the size of friends’ networks as well. By expanding the networks, the share of contacts users are truly interested in decreases and perception of information overload becomes inevitable. Among the qualitative properties of relationships, tie strength is found to be the foremost determinant of information relevance, followed by current and past communication intensity and attraction. Additionally, depending on the context, geographical distance can either mitigate or exacerbate information overload. Summary of possible network-based cases of information overload is presented in Table 6 with distribution of quotations and examples for each category.

Table 6 Network Characteristics as Sources of Information Overload

Network Characteristics	Relationship Characteristics
Network Size [16] <i>"Like this girl has 700 friends and she has like hundreds of things showing here. And I don't like it"</i>	Tie Strength [45] <i>"He is a close friend, so I trust that all this information is valuable... But this friend I hardly know, so you know..."</i>
Friends' Network Size [4] <i>"Because it's not what he posts, he was tagged, and I don't know who tagged him, probably somebody I don't know, so it's not really interesting"</i>	Attraction [11] <i>"This girl is really fun, so I would probably see what's going on... she's a nice person, I like her"</i>
Network Structure [6] <i>"It's like my work colleagues, my classmates, they are my other friends and I really don't look forward to know about them"</i>	Communication Intensity [7] high: <i>"I check mostly the people I interact with everyday..."</i> low: <i>"I know what my classmates are up to more or less, we attend the same parties, there's not that anxiety to see..."</i>
Geographical Distance [15] low: <i>"This could be more interesting, because she is in my city..."</i> high: <i>"Important is to get updates from friends who live far away"</i>	

Dynamics between various causes of information overload reveal several interesting patterns. First, combined information and network sources exacerbate the perception of information overload: *"I do not want to hear that one of the people I knew 5 years ago just woke up, or somebody is tired or whatever..."* (Q). Second, some sources can override others in their influence on information overload. For example, even if combined with high relationship level, high frequency of postings can cause information overload: *"This guy is my best friend in Turkey, but he is always posting this stuff like songs, or events, or when he is going to play on the radio, but I don't really pay attention as this is not important for me"* (Q).

Intervening and Driving Conditions

Intervening conditions limit the impact of causal conditions on the phenomenon and thus interfere with actions and strategies (Matavire and Brown 2008). In our study *time pressure*, *social pressure*, *bounded rationality*, *effort*, *skills and knowledge*, as well as *technology* can either exacerbate the perception of overload and call for more urgent and radical measures, or moderate it and thus constrain the strategic

moves. For example, time pressure can change perceptions of information relevance: *“On a hectic day I wouldn't follow the xyz I'm not really interested in... But when I have my holidays I just go and look at people”* (Q).

Driving conditions generally have a mitigating influence on the perception of information overload, and thus constrain actions and strategies. Consistent with previous findings, factors such as information longing (Boyd 2008), keeping in touch and facilitating contact (Krasnova et al. 2010a), social capital (Ellisson et al. 2007) emerge as relevant driving conditions. For example, information longing can diminish the perceptions of overload: *“I have a lot of friends, and I barely communicate with them. It is just for convenience, you always get the information...”* (Q). Timely information facilitates contact and assists in obtaining social capital referring to value that stems from relationships with others: *“Maybe if I read something interesting like this, I will contact them and ask for help...”*(Q).

Strategies and Actions

In order to deal with information overload, users apply different information processing strategies. Whereas passive strategies do not demand a lot of effort, active strategies require user involvement and have a direct impact on the network. Following continuous experiences with information overload, advanced strategies can be employed. Appendix 1 summarizes identified strategies and presents example quotations.

Cognitive heuristics, or relying on simple persuasive cues to identify relevant information, is usually employed in conditions of low motivation and limited ability to process the incoming information, as supported by evidence (Sicilia and Ruiz 2010). Depending on individual preferences and experience, Facebook users rely on friend-based, distance-based, interest-based, self-centered or explicit cues. Another important strategy – hiding – effectively helps overcome the problem of social pressure as opposed to deleting a person: *“If I delete him, he might think 'he does not want to know me anymore or what', but that function 'hide' is great”* (Q). A logical solution to information overload would be to promote self-responsibility for posting behavior, but, unfortunately, is hardly implementable: *“It's useless. Even if I don't share it, somebody else would share it two days later, or maybe shared one month earlier”* (Q).

Various intervening and driving conditions complicate the implementation of strategies. For example, intentions usually remain unfulfilled due to absence of necessary skills and unwillingness to invest effort: *“I do not hide them. I do not know, how that works. Maybe that would be a good idea. I am too lazy”* (Q). On the positive side, information longing can constrain account deactivation: *“Sometimes it is getting on my nerves so much that I think of deleting my account, but then I am too curious about the others”* (Q). Bounded rationality leads users to rely on certain heuristics when weighing the benefits and costs of adding another contact to their list: *“If I don't like the person, of course I don't accept, but if I don't care, or I just know him, I accept... You do not know how much he will post anyway”* (Q) – thus complicating the ex-ante network control.

Consequences

Action and interaction strategies may lead to a set of positive or negative, direct or indirect, latent or vivid

outcomes. Failure of strategies to deal with information overload usually leads to reduced levels of activity on the Newsfeed: *"I realized that I don't often go through all this, only if I have nothing else to do"* (Q). Repeating inability of the Newsfeed to provide users with relevant information changes user attitudes to the Newsfeed and urges them to turn to more traditional means of communication: *"I don't really pay attention to the Newsfeed anymore, because if there is something very important, they can contact me directly to make sure I get the message"* (Q). The disregard of the Newsfeed as a reliable source of information tarnishes its intended intermediary role: being less personal than a direct message and more private than a general blog.

Action and interaction strategies can exert indirect influence on individual social capital. When users delete or even hide others, the probability to obtain social capital in the future drastically decreases: *"If I am interested in this person, if I think that I will connect them again, then I don't hide. Only the people from the history, which I am not interested after all, but still spamming too much"* (Q). However, anticipation of future benefits and needs is usually constrained by incomplete information and bounded rationality.

Even though perceived change in information load can be achieved as a result of several strategies, information quality rarely improves: *"After you cleaned up your network did you feel the difference? - Not really. Well, maybe there is less posting, but still kind of like yeah..."* (Q). Ironically, even after action reversal users often face the same IO: *"I want to see what is going on, maybe something new happened, then I activate it back and after two minutes I realize that nothing new happened, same people writing the same useless messages around"* (Q). Finally, inability to cope with the network may result in feelings of lost control and dissatisfaction: *"I have like 500 friends... It is a lot, way too much to know who they are..."* (Q).

2.4 Discussion

The study identifies the context in which information overload occurs on SNS by applying grounded theory methodology. We find that users themselves are a major source of information overload, as they maintain large networks of loosely related and emotionally distant acquaintances. Being unable to anticipate and control the actions of others, as well as constrained by network functionality, users can hardly deal with information overload on the individual level. This calls for global measures on the part of the provider. By learning from past behavioral patterns and integrating user preferences, intelligent filters could provide SNS users with relevant information and thereby improve their experience on the platform.

Individual information filtering tools to relieve information overload already exist on Facebook, which allow to differentiate users into groups and set preferences for information presentation. However, users rarely utilize them due to ignorance, lack of skills, constraints of time and unwillingness to undertake effort: *"I would not put so much effort in creating those groups, I am lazy..."* (Q). In fact, users desire tools that help them filter information with least effort possible (Ariely 2000), urgently calling for some sort of intelligent filtering of the information on the Newsfeed without user interference: *"If they would*

introduce some kind of relevance measurement, which would work automatically, I don't want to be involved in this" (Q). Acknowledging the fact that Facebook has already done first steps in this direction by differentiating between Newsfeed and Livefeed, more changes are needed to ensure relevant content is delivered to the user at all times.

Design of intelligent filtering mechanisms rests on the problem of identification of individual perceptions on what is considered relevant at a specific point in time. Our study shows that relevant information usually originates from: 1) close friends at different geographical distances; 2) wider circles of friends with matching interests; and 3) any friends who share new and important information. User browsing and communication history can deliver valuable insights on what was considered relevant in the past and help predict future attitudes. Moreover, certain static information such as basic profile, fan pages and group memberships can be used to identify preferences. Location can be inferred from the profile and through usage of SNSs on mobile devices. In order to determine the novelty of information, such 'buzz' words could be searched for as: 'moving', 'marriage', 'daughter/son', 'new', etc. Based on these insights complex machine learning algorithms can be designed to ensure more relevant information is provided to users.

3 Empirical Studies

3.1 Theoretical Background

In this part of the dissertation we want to understand how users process information on SNS and which factors play a significant role in this process. Information processing refers to individual's cognitive processes, such as screening, comprehending, evaluating, interpreting and using information (Schick et al. 1990). Indeed, certain cognitive resources need to be activated in order to process information inputs into outputs, such as: attention and motivation, retrieval of certain knowledge structures from memory, comparison of obtained information with existing structures (Driver and Streufert 1969). The cognitive effort of reading a single post may be minimal, but on the Newsfeed users are faced with a lot of information every day: Facebook reports that each user creates ca. 90 pieces of content a month. Large amounts of input (Schneider 1987) and its possible complexity (Driver and Streufert 1969) increase the processing demands and may result in information overload which we have explored in the previous part. The feeling of information overload deprives users of the ability to attend to every message that is posted and forces them to adopt certain strategies to select the information they like and find useful.

Depending on the amount of available resources, time and motivation to process information, on the one end of information processing continuum is the heuristic and on the other - systematic information processing strategy (Bohner et al. 1995). Systematic processing is a bottom-up approach, involving extensive evaluation of arguments and issues involved in a message (i.e. its content) and comparing that information to existing knowledge structures and beliefs (Bohner et al. 1995) in order to arrive at an evaluative judgement. For systematic processing of information, a significant amount of motivation, ability

and cognitive resources are required. In contrast, the top-down heuristic processing strategy involves reliance on certain cognitive heuristics – rules of thumb, schemas or other stereotypes – to form attitudes. Cognitive heuristics are mental shortcuts that allow people to form opinions without extensively analysing the contents of the message based on certain cues present in the situation. Under this approach attitudes are formed based on the availability of heuristic cues, without any conscious effort (Ajzen and Sexton 1999).

Cognitive heuristics are gained through past experiences and observations, stored in memory and activated when the message reflects a certain feature – a heuristic cue - that signals its relevance (Chaiken 1980). Users have been found to increasingly base their social judgements on easily processed heuristics when the appropriate heuristic cues are available. Examples of widely employed heuristics, confirmed in numerous experiments, include: “consensus implies correctness” (Maheswaran and Chaiken 1991), “people agree with those they like” (Chaiken 1980), “length implies strength” (Wood et al. 1985), or “expert statements can be trusted” (Chaiken 1980). For example, through past experiences people can learn that a statement that achieves a consensus among a group of people is typically accurate. Thus, with this “consensus implies correctness” heuristic in mind, when faced with a message that reveals the agreement of other individuals on a certain issue (heuristic cue) individuals will tend to simply agree with others (apply the heuristic and form the corresponding attitude). Thus, the individuals form their opinions quickly and efficiently without engaging in extensive evaluation of the content. Other experiments show that people agree rather with likable than unlikable message communicators (Chaiken 1980), favour messages containing nine as opposed to three arguments (Wood et al. 1985) or employ other kinds of knowledge structures and stereotypes as their heuristics.

It is interesting to explore whether users process information heuristically or systematically on SNS. On the one hand, the theoretical insights might suggest that users might be prone to rather process information heuristically. First of all, as users are overloaded with the social information they receive each day, they are unable to process each piece of information systematically. Second, as people are economy-minded individuals, they prefer less effort to more effort, choosing heuristic processing as the default processing strategy (Bohner et al. 1995). Authors find that users will engage in systematic processing only when the personal relevance of the information is high (Ajzen and Sexton 1999). Third, the desired confidence level in the formed attitudes towards the posts on the Newsfeed is quite low, as information processing on such social applications as Facebook is usually not very task or goal-oriented (Sundar et al. 2007). Thus on the Newsfeed the sufficiency threshold – referring to the trade-off between the necessary effort and desired confidence level – is set low enough so that it can be achieved by the heuristic processing alone (Bohner et al. 1995). Finally, the posts on the Newsfeed are very rich in heuristic cues, such as the “sender” of the post, the ratings and comments it receives, type, length, etc. and can easily provide mental shortcuts to users when they are forming their attitudes.

On the other hand, our qualitative study supports both information processing strategies. First of all we find that users increasingly rely on friend-based, interest-based, distance-based, self-centered or explicit cues to identify relevant information: *“Usually I check my close friends, or the people I like most...” (IQ).*

However, would they then process the information heuristically (by simply valuing it more) or will they engage in a more complex process of information evaluation? Although the theory of information processing suggests that highly relevant information is processed rather systematically, the insights of the qualitative study do not offer an unambiguous conclusion. On the one hand, systematic processing might be applied, if the subject matter is personally relevant to the person: *“This could be something more interesting because she is talking about Econometrics, and I am also taking Econometrics, so it's interesting for me to look at it... oh, no, actually I am not taking this class, so I click away...” (IQ)*. On the other hand, people tend to simply value the information from their closer friends more without engaging in determining whether it has any value for them or not: *“I just clicked “like” because I knew it was from, I did not really read what it said” (IQ)*. Therefore it becomes important to explore which heuristic cues people use and what impact they have on information value.

As users would rather process information heuristically on SNS, we need to identify the heuristic cues they use and the impact they have on the value of information exchanged on SNS. For example, on the newsbots, such as Google News, people rely on heuristic cues to process large amounts of presented news stories, such as: name of the source, recency of the story and the number of related articles (Sundar et al. 2007). What concerns SNS, some of the heuristic cues were identified in the qualitative study presented above. Most of the factors identified as the causal conditions in the model can be used by users as heuristic cues. Similar to the qualitative study, we will differentiate between information characteristics and network characteristics in their impact on the value of information. The conceptual model presented in Figure 5 suggests that such information characteristics as post length or frequency of posting by others may increase the amount of information to process for users and thus result in information overload. Therefore, users might avoid processing posts which are too long or not pay attention to posts from people who post very frequently. At the same time, the network characteristics such as tie strength between the people or the high communication intensity with the person who posted the information might induce users to pay more attention to such information and thus highly evaluate it.

Coming back to the generic model presented in Figure 4 we would like to explore the impact of social information, contextual information surrounding the post, network characteristics with the person who posed the information as well as experience in using the medium and communication with the person. As discussed in section A2, these factors represent the most important heuristic cues that SNS users might employ to identify relevant information. Due to the absence of systematic research on the impact of these heuristic cues on information value in the context of SNS, in this part of the dissertation we aim to answer the following research questions:

- *How do characteristics of information impact the value of information on SNS?*
- *How do network characteristics impact the value of information on SNS?*
- *Which role does the experience of using the medium and communicating with others have?*

More specifically, in the first empirical study, we explore the impact of social information, tie strength and their interactions on the value of information users derive. Hereby we control for the general expe-

rience of using SNS and contextual information. In the second study, we explore the impact of contextual information as well as experience in communicating with the person who posted the information on the value of information from these people. In the subsequent sections we provide the explored empirical models, as well as the argumentation for the inclusion of the factors and their hypothesized relationships with information value. To test our models, we use both regression analysis in empirical study 1 as well as structural equation modelling in the empirical study 2 and thus provide rigorous findings on the relationship between different heuristic cues and information value people derive.

Dependent Variable – Information Value

The dependent variable in both studies we use is the perception of the subjective value of information on SNS. The model of Fishbein and Ajzen (1975) postulates that value is a function of beliefs that the object of evaluation possesses certain desired attributes and the importance of these attributes to the person. Applying the model of Fishbein and Ajzen (1975) to SNS, value of information is a subjective belief of users about the probability of positive outcomes associated with processing information on SNS and the importance of these outcomes for the users. Thus, a perception of value might result from the expectation of certain positive outcomes associated with processing information, for example finding out something new (Williams 2006), increased sense of connectedness (Köbler et al. 2010) or social capital (Ellison et al. 2007). On the other hand, value may be perceived due to the high personal relevance of the content or of the source of the information. Value is the main component of the Theory of Reasoned Action (TRA) and Technology-Acceptance Model (TAM) models that determines the intention of, as well as the subsequent behavior of users.

Value beliefs are complex and can possess multiple dimensions, such as: intensity, importance, knowledge, accessibility and affective-cognitive consistency (Crites et al. 1994, Voss et al. 2003). Generally accepting the critique of the uni-dimensional structure of beliefs (Voss et al. 2003) most authors differentiate between affective and cognitive components of value (Ajzen 2005; Voss et al. 2003; Yang and Yoo 2004). Cognitive value refers to evaluations of the qualities of the information itself, whereas affective value focuses on how much the person likes the information and is emotionally attached to it (Ajzen 2005). Cognitive and affective dimensions can be operationally distinguished (Ajzen and Sexton 1999): empirical studies show that in different contexts some dimensions of value are more important. Especially in the context of technology acceptance, affective and cognitive dimensions are two separate socio-psychological constructs. For example, in the case of the spreadsheet technology, it is the cognitive, and not the affective value that is responsible for the behavioural intention (Yang and Yoo 2004).

Using the insights of the qualitative study provided above, on SNS both affective and cognitive components of information value play a role. Previous generations of digital communication technologies were implemented within organizations, so researchers were interested in the instrumental value of information provided, such as its usefulness for performing certain tasks (e.g., Constant 1996). In contrast, most SNS use takes place outside of organizational contexts and contributes to the flow experiences of users (Trevino and Webster 1992). Therefore, it may be important to measure the affective value of information, or

how enjoyable and likeable the user considers the information. Depending on the contents and other characteristics of the post, value may be determined rather by its cognitive or affective components (Ajzen 2001). For example, affective components play a significant role in the evaluation of information expressing feelings and emotional states such as: ‘I am so happy today’ or ‘I am off to Shanghai’, whereas cognitive components are responsible for determining the value of posts that contain some useful information: ‘Does anyone know a good doctor’ or ‘Today a new recipe is added to our assortment’. Differentiating between the two dimensions may allow us to uncover differing dynamics in information processing and the resulting value perceptions.

In the first study we explore how the information and network characteristics impact these two dimensions of value. Cognitive and affective dimensions can additionally exert a distinct influence on the resulting behaviour (such as commenting, rating or simply reading the post). In the second study we also explore the impact of the two dimensions of value on the behavioral intention of users with respect to the post. Our research questions are summarized as follows:

- *Which of the explored factors (social information, contextual information, network structure, experience) impact affective and cognitive value of information?*
- *How do affective and cognitive components of information value impact the behavioral intention?*

3.2 Study and Application DesignB1 & B2

In order to answer our research questions, the collection of data using the self-report of users that is mainly achieved through surveys was not enough. Our aim was to explore which information users like and find useful on the Newsfeed. In order to identify that, we designed and registered a Facebook application. Users had to log-in to their Facebook accounts and install the application, after which they were explicitly asked for permission to access 6 posts on their Newsfeed in real time. The posts were retrieved from the Facebook database using Facebook query language (structure similar to SQL), which is an API (application programming interface) provided by Facebook (Facebook 2011b). The application was programmed in PHP and data stored in a MySQL database. To ensure the correctness of answers, Spry framework for Ajax is used to check forms and show hints if an answer is missing. For best graphical results CSS is used to design the page as close as possible to the Facebook’s Newsfeed.

Out of all available posts on the user’s Newsfeed over the last 72 hours, 6 were randomly selected and presented for evaluation one at a time together with an integrated survey tool. Users were asked about their attitude towards the post as well as the person who posted the information (for survey questions, see Appendix 2), whereas the information about the post was collected by the application automatically. Therefore, we were able to combine the self-report of users, which is not available when only crawling the data, with objective data available on the network.

The invitations to take part in the survey were posted on numerous Facebook groups, as well as virally marketed through friends and friends of friends of the authors – thus exemplifying a snowball methodol-

ogy. As a reward for participating in the study, users were provided with the scores reflecting their Facebook usage patterns. Users were not provided with any monetary reward, to prevent possible bias in those who chooses to respond. In total, 158 people completed the survey. As each user evaluated up to 6 posts, 929 data evaluations were obtained. It was not possible to collect 6 posts from each person, due to constraints with Facebook as well as people themselves. This represented a problem, as for the methodology used in study 1 a “balanced” sample of responses is required. Therefore, for this study, after removing respondents with unbalanced number of posts (less than 6), 810 observations from 135 respondents were left for analysis. As the methodologies for the second and third study do not have strict assumptions on the balanced sample, the whole 929 data instances were used.

The items of the full survey are presented in Appendix 2. Most of the items used in the survey had to be adapted to the Facebook context. First the users were asked about their attitude towards the presented post. Attitude was measured on a 6pt scale, where the ‘neutral’ answer option was omitted in order to induce respondents to make their choice in a particular direction. This approach is justifiable as authors believe that if given the possibility to answer neutrally users might have over-preferred this option in order to avoid engaging in the complex process of attitude formation (Friedman and Amoo 1999). Second, participants had to answer questions relating to post characteristics, such as understandability and novelty of the post. Next, they were faced with as well as relationship characteristics with the “poster”. Additionally, frequency and duration of usage of Facebook and the demographics (gender, age and country of origin) were collected. The objective post characteristics were recorded by the application automatically: post type, the number of comments, ratings and the number of words. For each study presented below, a different set of variables were used.

Table 7 Frequency Distribution of Information Evaluations

Affective				Cognitive		
Valuation	Description	Freq.	Share	Description	Freq.	Share
1	<i>Dislike very much</i>	31	3.8%	<i>Very useless</i>	200	24.7%
2	<i>Dislike</i>	79	9.8%	<i>Quite useless</i>	177	21.9%
3	<i>Slightly dislike</i>	126	15.6%	<i>Slightly useless</i>	134	16.5%
4	<i>Slightly like</i>	301	37.2%	<i>Slightly useful</i>	180	22.2%
5	<i>Like</i>	190	23.5%	<i>Quite useful</i>	82	10.1%
6	<i>Like it very much</i>	83	10.3%	<i>Very useful</i>	37	4.6%
Total		810 ⁴	100.0%		810 ⁴	100.0%

⁴ - similar frequencies can be observed for the sample with the total 929 posts

3.3 Descriptive Statistics

In this section we provide descriptive statistics on the whole sample of users. Our sample of 135 people consists of 51% male and 49% female respondents. 80% of respondents are below 30 years old, with the age range from 21 to 55 years old. Considering that 70% of Facebook users are between 18 and 44 years of age (Morrison 2010) and 55.60% of Facebook users are female (Eldon 2010), our sample is representative for a significant part of Facebook population. Respondents are frequent users of Facebook: 82% log-in at least once a day, a quarter of whom have Facebook running in the background when they are online. Our respondents maintain considerably large networks: the mean number of friends is 242 and the median 196, which is higher than an average of 130 reported by Facebook (2011a). By and large, our sample is representative of largest segment of Facebook audience: young active users.

What concerns the evaluated information, the frequencies in Table 7 make the differences between affective and cognitive valuations vivid. Whereas 70% of posts are perceived as generally likable (like very much – slightly like), only 37% are perceived as generally useful (very useful – slightly useful). Especially at the edges the affective-cognitive evaluations rarely coincide: 24.7% of posts are rated as extremely useless, whereas only 3.8% are very much disliked. Likeability is thus either the result a post being entertaining, but useless (e.g. think of a link to a funny sketch on a video sharing site), or the post being useful (e.g. a status update of a friend indicating that she came back from vacation and wants to go out tomorrow evening). These descriptive findings strengthen the necessity to differentiate between the cognitive and affective dimensions to explore information processing on SNS and the factors that impact these two dimensions of attitude.

Table 8 **Frequency Distribution of the Behavioral Intention**

Level	Description	Freq.	Share
1	<i>Ignore and consider hiding</i>	35	4.3%
2	<i>Ignore</i>	202	24.9%
3	<i>Give a brief look</i>	291	35.9%
4	<i>Read attentively</i>	109	13.5%
5	<i>Read and “like”</i>	86	10.62%
6	<i>Read and comment</i>	87	10.74%
Total		810 ⁵	100.0%

What concerns the behavioral intention with respect to the post, the values reflected in Table 8 reveal that ca. 30% of information is ignored, 35% receives a brief look and another 35% is read attentively or even commented upon. As is already vivid from the Table 7 and Table 8, information value is correlated with

⁵ - this factor is only used in the first study, hence the frequency only based on 810 posts

the behavioral intention: affective value has a 0.7 and cognitive – 0.6 correlation with behavioral intention.

Table 9 Frequency Distribution of Tie Strength

Level	Description	Freq.	Share
0	<i>Don't know at all</i>	47	5.8%
1	<i>Hardly know</i>	154	19.0%
2	<i>Slightly know</i>	332	41.0%
3	<i>Quite well</i>	205	25.3%
4	<i>Very well</i>	72	8.9%
Total		810 ⁶	100.0%

One of the main network characteristics subjectively assessed by participants was tie strength which refers to the strength of the relationship between the respondent and the source of information, represented by their digital connection on the platform. The results in Table 9 reveal that this measure was symmetrically distributed around the middle option, reflecting that people mainly slightly know the people in their network, with comparable number of people they do not know at all or know very well.

Table 10 Summary Statistics for Information Characteristics

<i>N</i> = 135	Mean	SD	Min	Max	N
<i>Number of Ratings</i>	2.39	3.87	0	29	810 ⁶
<i>Number of Comments</i>	7.01	5.61	0	30	810 ⁶
<i>Post Type (Photos)</i>	0.16	0.372	0	1	810 ⁶
<i>Post Length</i>	15.49	26.63	0	270	929 ⁷

The information characteristics were directly drawn from the platform, the summary statistics for which are presented in Table 10. Ratings were operationalized as the total number of people on the SNS who positively rated (“liked”) the information when we asked the respondents to evaluate it. Comments were operationalized as the total number of comments posted in response to primary information at the time of the evaluation. The evaluated information, on average, received more comments than ratings, though the former measure also exhibited greater variability. Post length was operationalized as the total number of words (separated by spaces) that the post contained, whereby links were not counted as words. Length on average comprises 15 words, but also exhibits quite high variability. Posts that were presented to users for evaluation were of different types, such as: status updates, links, pictures. We wanted to control whether

⁶ - this factor is only used in the first study, hence the frequency only based on 810 posts

⁷ - this factor is only used in the second study, hence statistics are based on 929 posts

the post was a picture, as pictures are usually accompanied by less text, but at the same time can transmit a lot of information through visualisation. Post type was operationalized as a dummy variable in the models used (1 if the post was a picture and 0 otherwise).

Table 11 **Frequency Distribution of Communication Intensity**

Valuation	Description	Private		Public		Following	
		Freq.	Share	Freq.	Share	Freq.	Share
1	<i>Almost Never</i>	547	58.9%	475	51.1%	330	35.5%
2	<i>Rarely</i>	232	24.9%	242	26.1%	288	31.0%
3	<i>Sometimes</i>	106	11.4%	154	16.6%	214	23.04%
4	<i>Regularly</i>	33	3.6%	39	4.2%	71	7.64%
5	<i>Almost Always</i>	11	1.2%	19	2.1%	26	2.8%
Total		929 ⁷	100.0%	929 ⁷	100.0%	929 ⁷	100.0%

The experience factors that we include in the study can be differentiated between: the experience with the medium and the experience in communication with the person who posts the information. The experience with the medium was captured by the self-reported frequency and duration of use of SNS. We see that on average people use SNS once a day and extend their use to up to 30 minutes. We operationalized frequency as a dummy variable indicating whether the respondent used the platform more than once per day; the duration dummy variable indicated whether the respondent used it for more than 10 minutes per day.

Table 12 **Frequency Distribution of Posting Frequency**

Level	Description	Freq.	Share
1	<i>Not at all</i>	19	2.1%
2	<i>Not that much</i>	87	9.4%
3	<i>Somewhat</i>	359	38.6%
4	<i>Quite a lot</i>	344	37.1%
5	<i>Very much</i>	120	12.9%
Total		929 ⁷	100.0%

The experience of communication with a partner was captured by the questions about the frequency of communication through SNS with the person who posted the information. Hereby we differentiated between private communication (through personal messages or chat), public communication (by posting something on that person's profile, commenting or rating something that this person posts) and following the person's news on the Newsfeed. The frequency distribution presented in Table 11 reveals that people do not communicate with a majority of their SNS friends either privately or publicly. At the same time, people follow over 30% of others sometimes or more often. This highlights the fact that people are

communicating only with a subset of their network on SNS, but are keeping up to date with a larger portion of it.

Another experience factor on the end of the provider of information is posting frequency, which is operationalized as the perceived amount of information that the person shares with others on SNS. The frequency distribution presented in Table 11 reveals that people perceive that most friends the information from whom they evaluated post quite a lot or very much, which indicates that people are irritated by the growing amount of information coming from their friends on the platform, supporting the information overload hypothesis. This factor, however, can be considered biased to the side of the people whose information was presented for evaluation and does not consider those who do not post very often or no information at all on the network.

3.4 Model B1: Impact of Social Information on Information Value

Research Model and Hypotheses

As SNS users may be overloaded with the information they receive (Koroleva et al. 2010), they have to decide which information to focus on. Reliance on certain cues significantly eases information processing (Bohner et al. 1995). Any piece of information shared on SNS is accompanied by a myriad of social context cues, which were not always present in the previous generations of computer-mediated communication. Although several dimensions of social context are important, situational information—defined as the “features of the immediate communication situation” (Sproull and Kiesler 1986, p. 1495)—appears most salient for interpersonal communication. On SNS these features include the underlying relationship between the users sharing and receiving information as well as the opinions of other users in the network that are provided through ratings and comments. We argue that users will use these social context cues to determine the value of information on SNS.

As one important purpose of SNS is to connect users with each other (boyd and Ellison 2008), any piece of information that is shared on SNS is related to someone in the user’s network. Although the SNS platform treats all relationships as equal (one is either a friend or not), actual relationships are more nuanced, differentiated by the qualities of the underlying relationship. As opposed to previous generations of computer-mediated communication, however, SNS provides extensive information on the background of the person who shares the information: on the profile as well as revealed during the history of interaction which can be used to proxy the underlying relationship (Gilbert and Karahalios 2009). As SNS primarily serve to support existing relationships rather than newly formed online ones (Ellison et al. 2007), the underlying tie strength that online contacts represent may be an important factor for determining how users derive value from the information they obtain from SNSs. Although the networks users maintain on

SNS are quite large⁸, users communicate regularly only with a smaller part of their network (Ellison et al. 2011), which again may be determined by the underlying tie strength of their relationships.

The feedback mechanisms that are usually embedded in SNS platforms fulfill the role of social information – defined as the perceptions of others in the social network about the information that is shared (Fulk et al. 1987). On the one hand, social media use various rating mechanisms, such as affirmations (e.g., Facebook’s Like; Google+’s +1), binary decisions (e.g., Digg’s up or down), or continua (Amazon’s 1–5 stars). Many SNSs employ one-sided ratings, to prevent the propagation of negative feedback, which could lower the interaction of users with the medium, and report the number of people who have positively evaluated the information. On the other hand, comments are open-ended mechanisms that enable users to share their opinions verbally and provide more extensive feedback about the digital content. As users tend to be influenced by others (Bandura 1977), ratings and comments might help them evaluate the information that is shared. In e-commerce, consumers increasingly use written reviews by other users to make a variety of purchase decisions (Bickart and Schindler 2001; Dellarocas 2003). Alternatively, considering the increasing amount and varied quality of information on SNSs (Koroleva et al. 2010), social information might make certain information more salient to a user within the general information flow (Salancik and Pfeffer 1978) and help users to prioritize and process information in these environments.

The model explored in this study is depicted in Figure 6. It explores the impact of the three main social context cues – number of ratings, number of comments and tie strength – in determining information value. Recognizing that tie strength might be the most important cue for processing information, we not only explore the direct impact of these cues on information value, but also interactions between these variables. We assume that information from people with whom a stronger relationship is shared will not be processed in the same way as that from the weaker ties. At the same time, we control for the experience of users with the medium, by including subjective frequency and duration of use of SNS. The hypotheses regarding the relationships of these variables with the cognitive as well as affective value of information are elaborated upon below.

The measurement scales for the variables explored in the study are presented in Appendix 2. Not all variables collected in the study were used. In this study information value was measured unidimensionally: affective value was measured by the likeability of the post, whereas cognitive value – by the usefulness of the post. Second, in order to assess tie strength, respondents had to answer how well they knew the source of information on a 5pt ordinal scale. Number of ratings and comments as well as post type were collected by the application automatically. In the end of the survey, respondents were asked to state how often and for how long they use Facebook. The descriptive statistics for these variables can be found in section 3.3 of this part of the dissertation (Table 7, Table 9, Table 10). We proceed to derive the hypotheses in the next section.

⁸ - 130 connections (Facebook 2011), 180-300 connections (e.g. Ellison et al. 2011; Burke et al. 2010).

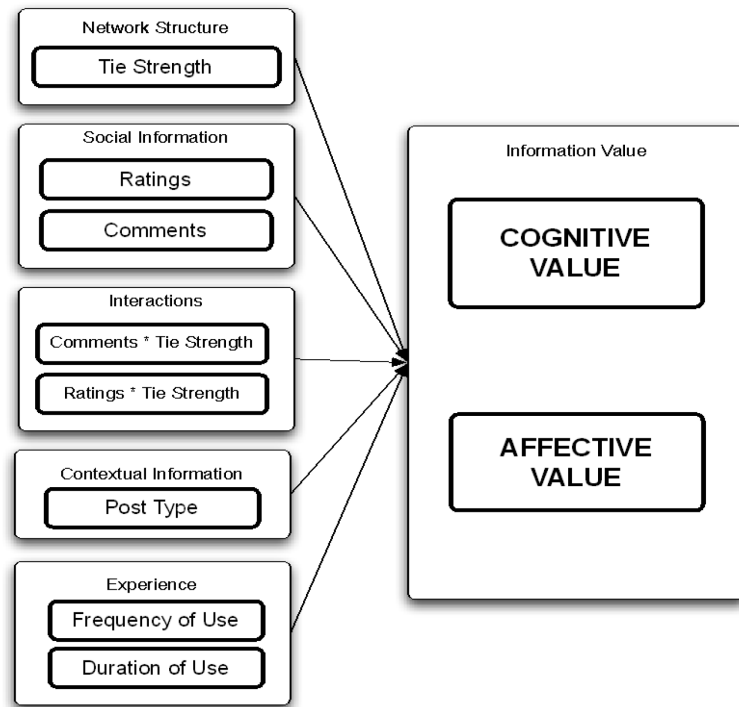


Figure 6 Research Model B1

Tie Strength

Social network analysis offers a productive lens for understanding how people obtain valuable information in communication networks. Many studies have investigated the influence of tie strength—defined as the frequency and depth of interaction (Marsden and Campbell 1984)—on the individual ability to obtain valuable information from a social network. Considerable debate persists regarding how tie strength relates to the information value provided by social networks in digital environments. Research suggests both that strong ties are better for obtaining information from networks (e.g., Coleman 1988) and that weaker ties are more valuable. For example, Granovetter (1973) finds that people are more likely to find valuable information about job searches through weak ties than strong ties, and Burt (1992) argues that weaker ties offer access to novel information, which often is valuable. However, the relative informational value of strong versus weak ties may depend on other factors, such as the pursued goal (Hansen 1999), type of information (Uzzi 1997), task (Rowley et al. 2000), or organizational structure (Oh et al. 2006, Reagans and McEvily 2003). Trying to resolve the conflicting views on the impact of strong and weak ties on information value, the later empirical evidence finds that both the diverse network of weak ties and a high bandwidth of communication with strong ties can provide users with diverse and non-redundant information, depending on the environment surrounding these ties (Aral and Van Alstyne 2012).

The application of social network theory to electronic communications tends to allow the weak tie expla-

nation to dominate assertions of information value derived from electronic networks. That is, weak ties appear primarily capable of communicating relatively thin content, such as text (Daft et al. 1987; Pickering and King 1995). Early empirical research supported this interpretation by indicating that the value users derive from information in a digital communication network could be predicted by weak tie theory (Constant et al. 1996). But more frequent communication among parties also might enable them to develop a shared understanding of the medium and thereby functionally expand the capacity of these channels for rich communication (Carlson and Zmud 1999). However, during public communication connections on SNSs receive all information contributed by the user, so it is unclear how each pair of users might develop shared usages that expand the channel—undermining traditional explanations of channel expansion theory (Carlson and Zmud 1999).

Although previous theory thus offers little clear guidance for how tie strength relates to the value of information, we could consider the rationale from previous IT-enabled communication research, which implies that weak tie theory applies to SNSs. The broadcast nature of public interaction makes it more amenable to short, shallow information updates. The limited number of nonverbal cues means that the contextual information provided by the platform still lacks depth compared with face-to-face interactions or sustained e-mail interactions with trusted others (Burke et al. 2011; Miranda and Saunders 2003). Some existing research on SNS supports the weak tie interpretation as well. SNS increases the number of weak ties due to the low cost of their maintenance (Donath and boyd 2004). Therefore, rather the benefits associated with bridging social capital, such as increase in new information, opportunities and perspectives have been found to result from increased SNS use (Ellison et al. 2007, 2011; Steinfield et al. 2008). Although originally intensity of SNS use was associated with emotional support from strong ties in the network (Ellison et al. 2007; Steinfield et al. 2008), the later studies disproved its potential (Burke et al. 2011; Vitak et al. 2011). On the one hand, it can explained by the fact that users may turn to alternative communication channels that would be more conducive for supporting their communication with strong ties (Vitak et al. 2011). On the other, the growth of networks is counter to the intimate environments necessary to communicate with strong ties (Vitak et al. 2011).

Despite this previous research, alternative rationales suggest that the value of information provided on SNSs also provide a compelling case for a strong tie interpretation, such that users would obtain more valuable information from strong ties. We find this line of argument more compelling, and argue that the strong tie interpretation may be more salient for understanding how users value information on SNS. First, whereas weak ties aid searches for information, strong ties are associated with better transfers of information (Hansen 1999). Social media platforms already automate many aspects of the search process, such as when a Facebook Newsfeed automatically gathers and prioritizes new information posted by members of the user's social network, so the user does not have to search through the profiles of every contact to find desired information. This information gathering function lowers information search costs and thus the value of weak ties. If the platform automatically identifies valuable information, the value that the user derives from that information should be closely associated with his or her ability to understand and then transfer that value, for which strong ties are more valuable.

Second, strong ties are particularly helpful for transferring tacit information, that is, information that is difficult to put into words (Hansen 2002). Tacit information may be particularly relevant on SNSs, where people frequently share multimedia images (e.g., photos) that contain implied information (e.g., identities, relationships, locations) and can convey more information to people with whom the user shares strong ties, who are better able to understand the tacit clues embedded in the photos. Furthermore, people often express incomplete thoughts on SNSs, such that the information appears cryptic to users who do not share tacit knowledge about a shared context (Koroleva et al. 2010). Tacit information conveyed through photos or required to understand cryptic text messages thus likely reveals little information to weak tie contacts, who may be unaware of its significance. Strong tie contacts should value this information obtained through SNSs more than weak tie contacts.

Third, the abundance of information makes it challenging for people to decide which information to pay attention to (Hansen and Haas 2001), which is also the case on SNS (Koroleva et al. 2010). In situations with abundant information, people prioritize information provided by strong ties (Carpenter et al. 2003); they also are more motivated by their strong ties (Krackhardt 1992), which may push them to pay attention to information provided by people with whom they have strong tie relationships. The uncontrolled nature of information sharing on SNS otherwise might discourage users from trusting information. With this logic, we hypothesize:

B1.1: *The strength of the tie between the respondent and the source of information relates positively to the perceived affective (1a) and cognitive (1b) value of information provided by that source.*

Social Information

Social information appears in two ways in extant literature. On the one hand, social presence theory emphasizes nonverbal cues, such as facial expressions, gestures, postures, or dress, which facilitate awareness of the other person during the interaction and thus the salience of the interpersonal setting (Short et al. 1976; Yoo and Alavi 2001). Media that transmit fewer such cues seem depersonalizing (Sproull and Kiesler 1986) and cannot be used to communicate complex (Dennis and Kinney 1998) or relational (Walther 1992) information. On the other hand, the social influence model explores the impact of behavior, statements, interpretations, and cognitive assessments by others in the social network on individual perceptions (Schmitz and Fulk 1991). Empirical studies confirm the impact of this sort of social information on technology adoption and use (Kraut et al. 1998), media attitudes and usage behaviors (Fulk et al. 1987), and opinions about job attributes and tasks (Thomas and Griffin 1983).

SNSs provide new types of social information that were not present in previous electronic communications. Users have opportunities to rate the information they interact with on the platform, which resembles a form of non-verbal response, as well as register their verbal responses on digital content in comments. By revealing the opinions of others in a social network, social information might affect the formation of users' opinions about information they receive through an SNS (Salancik and Pfeffer 1978). Alternatively, they might act as heuristic cues that focus user's attention (Ajzen and Sexton 1999). Previous theories emphasize the positive impact of any contextual cue on information value (Dennis and Kinney 1998) and

a linear relationship between the number of cues and the development of shared meaning (Miranda and Saunders 2003). On SNSs, however, these two types of social information might not be evaluated equally, due to the fundamental differences between them regarding: i) the processing effort needed to evaluate the information that contains them; and ii) the signals about agreeableness of the social environment on the information that is shared.

Ratings

Ratings on SNSs summarize the number of people who rate the information positively. In this respect, ratings on SNSs mirror nonverbal cues such as nodding in approval. Ratings are easy to process, provide positive signals as well as reveal the agreeableness of other users on the information that is shared, and thus should positively relate to information value.

First, as ratings are similar to nonverbal cues, they provide instant impressions of the information being shared. Ratings are easy to process and therefore can be easily employed as heuristic cues to identify relevant information. Ratings can make certain information more salient, by providing cues about which information to consider (Salancik and Pfeffer 1978). Feedback from others is particularly valuable for ranking, filtering, and retrieving content (Bian et al. 2008). Therefore, information that has been rated by many others may attract more attention and make it seem more significant in the overall information flow.

Second, many ratings reveal that users agree with the information that is being shared. Rating something positively is an easy form of non-verbal response that is employed when users do not have to add anything to the information that is shared. On the one hand, it might be a signal of the high quality of information itself. Indeed, on Facebook the number of positive ratings is associated with positive emotions expressed in the post (Schöndienst and Dang-Xuan 2012). On the other hand, if users see many others agree with the information that is shared, they might tend to positively evaluate it themselves as well. When faced with a majority preference, people likely assume that evaluation is correct and adopt it as their own preference (Dennis 1996). Users rely more on others' interpretations especially when evidence is unavailable or ambiguous (Festinger 1954) or if they are not motivated to evaluate the information systematically (Ajzen and Sexton 1999). Therefore, user preferences may be shaped by the simple number of people supporting a position, rather than the quality of the information (Dennis 1996). With a so-called bandwagon heuristic, users tend to grant the highest ratings to information selected by many others (Sundar and Nass 2001). Using this logic, we hypothesize:

B1.2: *Ratings relate positively to the perceived affective (2a) and cognitive (2b) value of information on SNS.*

Comments

Comments are open-ended mechanisms that enable users to share their opinions verbally and provide more extensive feedback about the digital content. Unlike ratings, which can be issued only once, comments allow for multiple exchanges between parties and thus increase the depth of shared information (Miranda and Saunders 2003). Compared to ratings, however, comments are more cumbersome to

process and might also reveal a disagreement of other users on the information being shared, and thus might coincide with negative evaluations of information.

First, comments are verbal responses, which must be processed extensively. Although they provide more elaborate evaluations of shared information, their verbal nature and the inability to summarize comments as effectively as ratings may create an information overload (Schultz and Vandebosch 1998). To evaluate information, the user must evaluate the original information, as well as the value and validity of each subsequent comment. Because SNS users often contribute comments simultaneously and are not limited in the number of verbal symbols they use, more information gets exchanged on the network (Dennis 1996; Schultz and Vandebosch 1998). More contributors tend to lead to decreasing marginal value (Asvansund et al. 2004; Schroder et al. 1967); that is, additional comments require similar amounts of information processing but produce less insight. Moreover, the quality of comments itself is questionable: on the one hand, computer-mediated communication encourages people to share ideas without editing, structuring, or prioritizing them (Weick 1985), and on the other - users might have different motivations to provide comments, such as deliberate promotion or demotion of content, attracting attention, and so forth (Bian et al. 2008). Compared to ratings, comments are much harder to process and therefore users might be reluctant to process them systematically and simply evaluate information that has received a lot of comments negatively.

Second, comments might reveal that other users do not agree with the information that is being shared. Users exert effort to make comments, instead of simply rating the information, which implies a more complex response. As a form of verbal feedback, comments are used to clarify content, complete a statement, or express a controversial opinion (Dennis and Kinney 1998) – that is either add information to or provide an alternative view on the information that is shared. Thus, information that sparks many comments likely signals disagreement, controversy or incompleteness. Indeed, on SNSs, high number of comments is associated with negative emotions expressed in the post (Schöndienst and Dang-Xuan 2012). In e-commerce, more comments indicate contradictory advice (Gershoff et al. 2003). Information may be evaluated more negatively if it is incongruent (Maheswaran and Chaiken 1991) or others appear to oppose the message's position (Chaiken et al. 1989). Thus, instead of systematically evaluating the comments in order to arrive at the evaluative judgment of the information that is shared, users might value the information with many comments less. Thus, we hypothesize:

B1.3: *Comments relate negatively to the perceived value of information on SNSs.*

Interactions

Because social information cannot be separated from the source of the information (i.e., the underlying relationship between the source and the respondent), we must consider how these contextual cues interact to influence information value on SNSs. On the one hand, tie strength and social information might have additive impacts on evaluations, such that the two cues lead to higher evaluations than if just one was considered (Chaiken 1980). In this case, the positive effect of ratings on information might be enhanced by a stronger relationship with the source of information. On the other hand, the negative effect of com-

ments could be offset (or exacerbated), depending on the strength of the relationship. For strong ties, the probability that the comments come from stronger ties increases, so the negative effect of information overload might be offset by familiarity and an established shared context with the commentators. For weak ties, the probability that the comments are from weak (or even unknown) ties increases instead, so the negative effect of information overload may be exacerbated by the lack of familiarity.

However, the cognitive effort associated with evaluating information on SNSs might limit users' motivations to evaluate the impact of all contextual information additively (Fiske and Taylor 1991). Therefore, the principle of sufficiency might offer a more realistic description of information processing in conditions of increasing information flow (Bohner et al. 1995): If one contextual cue delivers sufficient information, other cues might not matter. This principle receives empirical support in a news processing context, though if a source is not sufficiently credible, users will consider other cues to form opinions about which news to read (Sundar et al. 2007). We propose a similar effect for SNS-based information evaluations. Specifically, tie strength should be the primary determinant of information value, such that people prefer to focus on their stronger ties (Carpenter et al. 2003), with whom they share meaning and can evaluate information easily. However, if time and motivation remain, they may consider information from their weaker ties, and as this information demands more effort to process, they would increasingly use ratings and comments from others in the network to evaluate it.

We posit that tie strength overrides the impact of social information for several reasons. First, social information requires more effort to process, whereas a relationship is salient and prompts automatic assessments. Second, social information reflects the opinions of others in the social network, which may not coincide with the trusted social network of the respondent. If the tie is strong, the shared meaning, already established through a long process of relationship development, is enough to produce positive evaluations of information, without needing to include others' opinions. With weak ties, the lack of shared meaning requires users to rely on other available cues, such as social information. Therefore, we hypothesize:

B1.4: *The weaker the relationship with the source of information, the more influential are the ratings and comments provided by other users to evaluate information from this source.*

Contextual Information: Post Type

SNSs allow users to share not only text but also pictures, music, and videos, which might provide additional cues to recipients of information. The type of the post - status update, link or photo – is likely to be important in determining user attitudes. Users are likely to especially process multimedia content differently than textual information. Underscoring the importance of this type of content, the photo application on Facebook generates twice as much traffic as the next three largest photo sharing websites (Burke et al. 2009). Users might employ post type as a form of contextual information heuristic to identify valuable information. By being able to visualize large amounts of data effectively (Bederson and Schneiderman 2003), pictures can trigger the well-known “a picture is worth a thousand words” heuristic, and induce users to evaluate them positively. Compared to text, pictures offer more value for the same processing cost. We hypothesize:

B1.5: *Pictures will have more affective (5a) and cognitive (5b) value than other types of content, such as text, on SNS.*

Experience with the Medium

Although SNSs do not expressly capture the strength of the ties between users, the frequency and duration of their interactions with the platform may affect a respondent's ability to process information obtained on the platform. The frequency and duration of using a medium has been found to relate positively to the perceptions of richness of the medium, and with it, the value of information exchanged through this medium (Carlson and Zmud 1999). The more users interact with the medium as a whole and with others in particular, they gain experience in communicating with others, develop a shared meaning and learn how to interact with them. Moreover, people acquire more transactive information – that is information on who knows what and what can one learn from the network. Therefore, more intensive use of the network should be related with higher perceived information value. We control for the experience of users with SNS by including the self-reported frequency and duration of SNS use. We operationalized frequency as a dummy variable indicating whether the respondent used the platform more than once per day; the duration dummy variable indicated whether the respondent used it for more than 10 minutes per day.

B1.6: *The frequency (6a) and duration 6(b) of SNS use will relate positively to the value of information.*

Empirical Operationalization

In our empirical strategy to test our hypotheses, we started by constructing a linear model of the information value derived from a post. The latent variable representing this information value comprised three components: (1) the post-specific characteristics, (2) respondent-specific characteristics, and (3) a random disturbance term. We can estimate the model using three specifications that differ in their assumptions about the relationship between the latent variable that governs information value (y^*) and the observed respondent valuations (y), as well as how they controlled for respondent characteristics (ξ).

The primary specification—a random effects ordered probit—enabled us to treat respondents' valuations as ordinal and control for respondent-specific characteristics by including a random effects term. The other two specifications instead make an explicit estimation of the latent variable y^* using polychoric principal component analysis (PCA), such that they function as a robustness check. The panel-generalized least squares (GLS) approach controlled for respondent-specific characteristics with fixed effects; the simple pooled ordinary least squares (OLS) method instead included explicit control variables. We depict our methodological approach in Figure 7. By using three distinct methods to verify the hypotheses, we confirm that our results are not driven by the specification but rather by underlying patterns in the data.

To construct the underlying model, we assumed that the information value a respondent derives from a post, measured by the respondent's Likert scale valuation of each specific post (y), depends on the latent variable y^* , which offers a linear function of a set of respondent-specific characteristics (ξ), post-specific characteristics ($X'\beta$), and the random post-specific disturbance term (ϵ). That is,

$$y^* = X'\beta + \xi + \epsilon$$

The columns of a $k \times n$ matrix X contain the explicitly included variables; the $k \times 1$ vector β includes the set of coefficients, where the sign of β_k indicates the relationship between the k^{th} variable and the information value that the respondent derives from that post. Because each respondent evaluated six different posts, we could apply panel-data methods to eliminate respondent-specific influences, ξ , when estimating the vector β . The variables included in the X columns were tie strength (0–4), ratings (number), ratings \times tie strength, comments (number), comments \times tie strength, and post type (1 = post is a photo, 0 = otherwise).

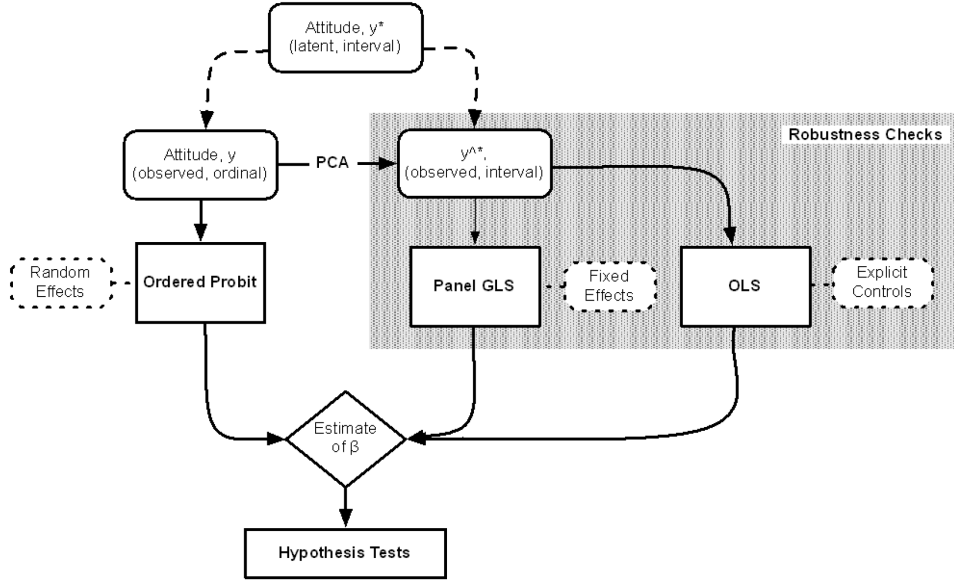


Figure 7 Methodological Approach of Model B1

For the first method, we estimated an *ordered probit* specification (Greene 2000) directly on the respondent's post valuations, while controlling for respondent-specific influences, ξ , by including the user-specific random effects (Butler and Moffitt 1982). The advantage of using a limited dependent variable regression approach in this context is that the observed (ordinal) valuation need not be treated as an interval variable for the hypothesis tests. The assumed relationship between the observed Likert scale valuation of post j by respondent i , $y_{ij} \in \{0, 1, 2, 3, 4, 5\}$, and the latent variable y_{ij}^* is characterized by a set of unobserved cut-off points, $\{\mu_0, \dots, \mu_4\}$. As y^* moves beyond a cut-off point, the observed ordinal variable moves up one category. Formally, we represent the relationship between the latent variable y_{ij}^* and y_{ij} as:

$$y_{ij} = \begin{cases} 0 & y_{ij}^* < \mu_0 \\ 1 & \mu_0 < y_{ij}^* < \mu_1 \\ 2 & \mu_1 < y_{ij}^* < \mu_2 \\ 3 & \mu_2 < y_{ij}^* < \mu_3 \\ 4 & \mu_3 < y_{ij}^* < \mu_4 \\ 5 & \mu_4 < y_{ij}^* \end{cases}$$

In turn, we estimate the set of parameters $\{\beta, \mu_0, \dots, \mu_4, \sigma_\xi^2\}$ jointly using maximum likelihood, where σ_ξ^2 is the variance of the respondent-specific random effect.

The second method used PCA to reduce the two ordinal measures of information value (i.e., affective and cognitive) to one interval variable, \hat{y}^* , which then serves as the estimate of the latent variable y^* . Because our dependent variable y is ordinal rather than interval, we use polychoric PCA, which is geared toward ordinal variables (Kolenikov and Angeles, 2004). Specifically, we postulate that our two observed evaluations, y_{pi} for $p = \{\text{Affective, Cognitive}\}$, are governed by two latent variables, y_{pi}^* , that follow a joint bivariate normal distribution with standard normal marginals and correlation ρ . The observed ordinal ratings y_{pi} then can be obtained by discretizing y_{pi}^* . Formally:⁹

$$y_{pi} = \begin{cases} 0 & y_{pi}^* < \alpha_0 \\ 1 & \alpha_0 < y_{pi}^* < \alpha_1 \\ 2 & \alpha_1 < y_{pi}^* < \alpha_2 \\ 3 & \alpha_2 < y_{pi}^* < \alpha_3 \\ 4 & \alpha_3 < y_{pi}^* < \alpha_4 \\ 5 & \alpha_4 < y_{pi}^* \end{cases}$$

The estimate of the correlation coefficient ρ , $\hat{\rho}$, can be obtained by maximizing the following log-likelihood for $\{\rho, \alpha\}$, given the observed valuations $y_{\text{aff},i}$ and $y_{\text{cog},i}$

$$\log L(\rho, \alpha; y_{\text{aff},i}, y_{\text{cog},i}) = \sum_{i=1}^n \log \pi(y_{\text{aff},i}^*, y_{\text{cog},i}^*; \rho, \alpha)$$

where $\pi(l, m; \rho, \alpha)$ represents the cell probability $\text{Prob}[y_{\text{aff}} = l, y_{\text{cog}} = m; \rho, \alpha]$. After obtaining $\hat{\rho}$, we can proceed to populate the correlation matrix and employ standard PCA techniques (Härdle and Simar 2007).

The first principal component, \hat{y}^* , is linearly regressed on X , controlling for the respondent-specific influence ξ , by including a respondent-specific fixed effect. The use of fixed effects, which is not possible in an ordered probit specification, offers the advantage of robustness in the presence correlation between the set of explanatory variables X and the respondent-specific effect ξ . This robustness comes at the price of efficiency though (Wooldridge 2002). In addition, a robust covariance estimator (White 1982) helps alleviate any potential misspecification of the estimator covariance matrix induced by our procedure.

In the final empirical specification, all the observations were pooled, and we performed a regular cross-section OLS regression. The explicit control variables address the respondent-specific effect issue, rather than random or fixed effects. This pooled OLS regression functions as a final robustness check on our findings, as well as a vehicle for performing heteroskedasticity and multicollinearity diagnostics. However, we also note that the ordinal random effects procedure is methodologically the most correct, and we base our inferences on these results. As we indicated previously, the two regressions mainly serve to pro-

⁹To estimate, we pooled all observations, such that the subscript ij gets replaced by i .

vide additional diagnostics and ensure that our results are not driven by the use of a random effects ordered probit specification or, more broadly, the use of unobserved heterogeneity corrections (i.e., random or fixed effects).

Estimation Results

The estimation results in Table 13 reveal that for both affective and cognitive valuations in the two random effects ordered probit specifications (first two columns in Table 13), tie strength significantly (1% level) correlates with positive valuations, though this correlation is more pronounced for affective valuations. These results confirm Hypothesis B1.1. In addition, the number of people who rated the information correlates positively and significantly (1%) with both affective and instrumental valuations, in support of Hypothesis B1.2. The negative correlation of the number of comments is only significant (1%) for the cognitive value of information and does not significantly relate to the affective value, so we only confirm Hypothesis B1.3a. Furthermore, the type of post matters for affective but not for cognitive valuations: photo posts are significantly (1% level) preferred to non-photo posts. We therefore support hypothesis B1.5a, and reject hypothesis B1.5b.

According to the pseudo- R^2 measure of fit (MacFadden 1974) the model is slightly better at explaining the cognitive (pseudo- R^2 : 0.063) than the affective (pseudo- R^2 : 0.045) information value. The reader should note that pseudo- R^2 are calculated on the bases of log-likelihoods and not percentage of variance explained, and as such can only be used for model comparison and not as a measure of fit. In addition, we find that that personal characteristics, as measured by rho - which indicates the percentage of unexplained variance accounted for by the respondent-specific error component, ξ , are more important in determining the cognitive dimension of attitude (rho: 0.226) than the affective dimension (rho: 0.152).

We also find that tie strength moderates the relationships between information value and social information. In the case of ratings, greater tie strength diminishes the positive relationship with information value, according to the negative point estimates of ratings \times tie strength, significant at the 10% level for affective and the 5% level for instrumental valuations. Similarly, for comments, increasing tie strength mitigates the negative relationship with information value, though this moderating effect is significant (10%) only for instrumental valuations. As this effect is not robust to changes in specification (columns 4 and 5 of Table 13), we only find partial support for Hypothesis B1.4.

With Figure 8 we depict the total estimated composite effects of tie strength and ratings for affective value. For example, we calculated the line that shows the total estimated impact of ratings on the affective value of information when the respondent knows the source very well by summing the estimated coefficient on tie strength from the first column of Table 13, multiplied by 4 (i.e., value of the tie strength variable), and then adding it to the estimated interaction term for the aforementioned level of tie strength. When we hold everything else constant, affective value is consistently high when the posts come from the respondent's strongest ties; the number of people who rate the information does not change this status significantly. As tie strength decreases, the marginal impact of ratings increases though. At the lowest value of tie strength, the slope of the total impact is at its steepest.

Table 13 Estimation Results of Model B1¹⁰

Variable	Ordered Probit		Panel GLS		OLS	
	Affective	Cognitive	Information Value	Information Value	Information Value	Information Value
<i>Tie strength</i>	0.391 *** (0.068)	0.297 *** (0.070)	0.362 *** (0.072)	0.392 *** (0.067)		
<i>Ratings</i>	0.091 *** (0.026)	0.100 *** (0.027)	0.111 *** (0.030)	0.109 *** (0.036)		
<i>Comments</i>	-0.017 (0.017)	-0.060 *** (0.019)	-0.044 ** (0.021)	-0.044 ** (0.024)		
<i>Ratings × Tie strength</i>	-0.019 * (0.011)	-0.022 ** (0.011)	-0.023 * (0.012)	-0.019 * (0.011)		
<i>Comments × Tie strength</i>	0.002 (0.007)	0.012 * (0.008)	0.007 (0.009)	0.007 (0.007)		
<i>Post type (picture)</i>	0.313 *** (0.102)	0.155 (0.103)	0.251 *** (0.100)	0.272 *** (0.109)		
<i>Frequency</i>	-	-	-	0.207 ** (0.106)		
<i>Duration</i>	-	-	-	0.153 ** (0.081)		
<i>Constant</i>	-	-	-0.77 *** (0.173)	-1.5 *** (0.239)		
<i>Rho</i>	0.152 ***	0.226 ***	0.278			
<i>pseudo R²</i>	0.045	0.063	0.144	0.155		
<i>N</i>	810	810	810	810		

Robustness Checks

As outlined above, we also performed a polychoric PCA on the two dimensions of information value, in order to test our hypothesis via a different method (see Figure 7). The polychoric PCA procedure yields a polychoric correlation estimate of 0.688, with an estimated standard error of 0.023. Both Pearson- and likelihood ratio-based measures of fit indicate that the correlation is statistically significant at 1%. If we use the resulting correlation matrix and apply the PCA procedure results to a principal vector that ac-

¹⁰ - *** Significant at 1%. ** at 5%. * at 10%, Standard errors in brackets.

counts for 84.38% of the variance in the two ordinal valuations. This principal component, which serves as an estimate of the latent variable y^* , is then regressed via Panel Ordinary Least Squares on the variables explored.

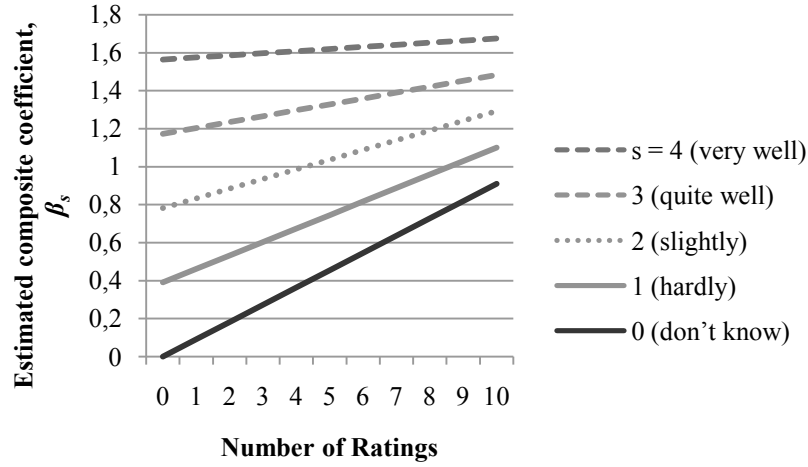


Figure 8 Composite coefficient and number of ratings at levels of tie strength

The estimates using the panel GLS regression method appear in the third column of Table 13. Using PCA and the fixed effects specification, we reproduce most of the results from the random effects ordered probit specification. That is, tie strength exhibits the strongest positive relationship with information value (1% level). Ratings significantly (1% level) correlate with information value, moderated by tie strength (10% level). The number of comments correlates negatively (5% level) with information value, and though the positive point estimate of the tie strength \times number of comments interaction indicates that this effect is moderated, the interaction term is not statistically significant. Because the interaction term was significant at the 10% level only in the ordered probit regression involving instrumental valuations, and all other effects of the ordered probit regressions coincide with the results of the panel GLS, we conclude that our findings were not driven by the estimation method. The overall fit of the model, as measured by the R^2 statistic, is 14.4%.

The estimation results for the pooled OLS regression, in the fourth column of Table 13, generally coincide with the results of the other specifications, again except for the loss of significance for the comments \times tie strength coefficient. All the observations are pooled, and thus we cannot use random or fixed effects to control for respondent-specific characteristics. Instead, we added a series of control (dummy) variables especially pertaining to the experience of users with the medium in general. We find that both frequency and duration of use (both at 5% levels) are positively related with the aggregated estimate of information value. Therefore, the more intensive users realize more value from information exchanged on SNS. The overall fit of this model, as measured by the R^2 statistic, is 15.5%.

In order to account for multicollinearity in our regression analysis, we calculate the variance inflation factors (VIFs), which indicate how much the variance of an estimated regression coefficient is increased because of collinearity. We calculated variance inflation factors from this last specification, but they do

not exceed the cut-off value proposed by Kutner et al. (2004), such that multicollinearity is not a concern. The Breusch-Pagan (1979) test for heteroskedasticity, taking the constant variance of disturbances as a null hypothesis, yielded a p -value of 0.17. Thus, heteroskedasticity also was not a concern in our specification.

We conclude that the ordered probit results presented earlier are, in fact, not driven by the employed econometric specification, as they are in line with the results derived through our robust panel GLS approximation for the two dimensions of attitude as well as the OLS regression with explicit controls. The reader should note that in this case we see that the standard errors in the panel GLS estimation results, on which the relevant p -value is estimated, are biased downwards, which is evident from the increase in the significance of all estimated coefficient tests when moving from the random effects ordered probit results to the panel GLS results.

Discussion

The paper makes several important theoretical contributions (the practical contributions will be discussed in section 5). In this study we test whether the tie strength of the underlying relationships, information provided by others in the network through ratings and comments, or a combination of these factors influence how respondents valued information provided by the SNS platform. We find that users increasingly utilize these factors as heuristic cues to identify relevant information on the platform. Specifically, users tend to value information provided by strong tie contacts more than information provided by weak tie contacts (Hypothesis B1.3, Table 13). Furthermore, ratings increase the value of information (Hypothesis B1.1, Table 13), but comments exert a negative impact on it (Hypothesis B1.2, Table 13). Finally, social information provided by the platform (i.e., ratings and comments) is more influential for valuing information provided by weak tie contacts than that from strong tie contacts (Hypothesis B1.4, Figure 8).

Previous research largely relies on weak tie lenses to understand how IT-enabled communication networks provide value to users (e.g., Constant et al. 1996; Pickering and King 1995). Previous studies have also emphasized the value of weak ties in SNS (e.g., Burke et al. 2010; Ellison et al. 2007; Vitak et al. 2011). However, our study shows that SNS place more value on information from strong rather than weak ties. Despite their ability to maintain relationships with a vast and diverse network of weak acquaintances in SNSs (boyd and Ellison 2008), users prefer to focus on their stronger ties and probably forgo some of the benefits of diverse and novel information associated with weak ties. Presumably, they do so because much larger networks than the average suggested by Dunbar (1992) tend to exist on SNSs, which would increase the costs of information processing from weak, rather than strong, ties. Alternatively, the established shared meaning with strong ties may improve people's ability to derive more value from these sources of information.

Whereas media richness theory suggests that both nonverbal gestures and verbal feedback promote the immediacy of communication (Dennis and Kinney 1998), we find that these types of social information have differential impacts on the value of information on SNSs. *Ceteris paribus*, the marginal impact of ratings on information value is positive, whereas comments are negatively associated with information

value. By effectively summarizing others' evaluations, positively directed ratings provide cognitive heuristics to identify relevant information: "the more other people like it, the more I like it too." Comments, on the other hand, might create information overload and cause users to value the information less, instead of spending time to determine who is right and who is wrong (Jones et al. 2004; Koroleva et al. 2010).

Although the impact of ratings is robust across all specifications we test, comments are only significant for cognitive evaluations. In general, the impact of ratings on the dimensions of information value is stronger than that of comments. This is probably due to the fact that ratings are positive evaluations and their impact on information value is unambiguous: the more people rate the information, the better. In contrast, the dynamics behind comments are not as clear. Although mainly comments are used to clarify the statement or express one's own opinion (i.e., add some new or contradictory information); sometimes comments can be given in affirmation of what is shared in the primary post (e.g. congratulate someone with something). As comments can be used with many different purposes, depending on the content of the primary post, we observe this ambiguous association with information value.

It is interesting to explore the impact of the possible combinations of ratings and comments on information value. Our findings suggest that information that has received a lot of ratings and a few comments will be evaluated positively, and information that has received a lot of comments and few ratings will be associated with negative responses. When information, however, possesses similar number of comments and ratings, our model cannot explicitly determine the impact on information value, although the presence of ratings the impact of which is less ambiguous than comments will tend to coincide with rather positive evaluations.

Furthermore, our results suggest the need for a much more nuanced understanding of tie strength and information value on SNSs. Specifically, consistent with previous research (e.g., Hansen 1999), we find that people tend to process information provided by strong ties and weak ties differently, even though the strength of these relationships is not embedded in or reported by the platform. That is, users are ready to process most information from their stronger ties, but will only process information with more ratings (and fewer comments) from their weaker ties. This can be due to the missing shared context with weak ties – users need additional indices to be able to process information from these ties - the role taken by social information as it depicts the opinions of other users and thus helps to evaluate information. The interaction effect of tie strength is more pronounced with ratings than with comments, though. This is due to the ambiguity of the dynamics involved in the impact of comments on information value discussed above, as evaluation of comments is more dependent on the content of the post than the person who shared it. That is, depending on the content, there can be situations where comments are necessary for processing any information or create information overload no matter who shares the information.

Additionally we have tested whether contextual factors and experience of using the medium influence information value. What concerns contextual information, we explored the impact of photo posts with respect to any other type of post on the network. We find the affective value of pictures to be higher than

that of any other information types exchanged on the network (Table 13), likely because pictures are able to depict large amounts of data effectively (Bederson and Schneiderman, 2003) and thus offer more value for minimal processing costs, compared with other post types. Moreover, photos can transfer contextual information, including nonverbal cues, which encourage awareness of other people during interactions with content on the platform and thus positively affect its value.

What concerns the experience with the medium, we find that both the frequency and duration of SNS platform use are positively associated with the value of information users obtain from the platform (Hypothesis 6, Table 13). Perhaps users who are more interested in the type of information provided by the platform simply use the platform more. Another explanation instead might entail an extension of channel expansion theory (Carlson and Zmud 1999): Although people do not necessarily expand the channel through their shared usage, they may spend more time cultivating networks and learning conventions for effective communication using SNS, such that they expand the channel through more effective network management.

We find that although highly correlated, cognitive and affective valuations are subject to distinct information processing mechanisms. Ratings play a significant role for the affective valuations, whereas both can have a significant impact on cognitive ones. This finding is quite intuitive, as on Facebook the positive rating in form of “likes” signals the affective state of others towards the post. At the same time for cognitive evaluations, both ratings and comments can be of use by providing additional information. This confirms the findings of Ajzen and Sexton (1999), who report that the two dimensions of attitude are subject to distinct psychological mechanisms and urges us to pledge in favor of two-dimensional categorization of attitude. At the same time, the high correlations between the affective and cognitive dimensions of attitude, revealed by the polychoric PCA results suggest that the three dimensions possess a certain overlapping “core” that is responsible for determining the overall information value on SNS. Additionally, we notice differences in the formation of attitude based on individual-specific effects. The analysis of ρ introduced in the previous section reveals that affective evaluations are less affected by personal characteristics and are more random, rather depending on various peripheral cues present in the situation. Cognitive attitudes are more solid, based more on the individual characteristics, for example, predisposition to look for information on SNS or past experience in obtaining useful advice, or certain interests in looking for information (Table 13, analysis of ρ).

3.5 Model B2: Impact of Information Characteristics on Information Value

Research Model and Hypotheses

In this part of the dissertation we explore the impact of the breadth and depth as the properties of information on the value of information exchanged on the network. The motivation behind studying the impact of information characteristics was elaborated upon in the introduction, section A2.2. Most of the factors we explore in this study have been identified as the sources of information overload in the conceptual model

presented in Figure 5. At the same time, we want to control for the experience of users in communication with each other, as argued in section A2.3. Moreover, we not only explore the impact of the information characteristics on the dimensions of value, but also address how value impacts the behavioral intention with respect to the post. The full research model is presented in Figure 9.

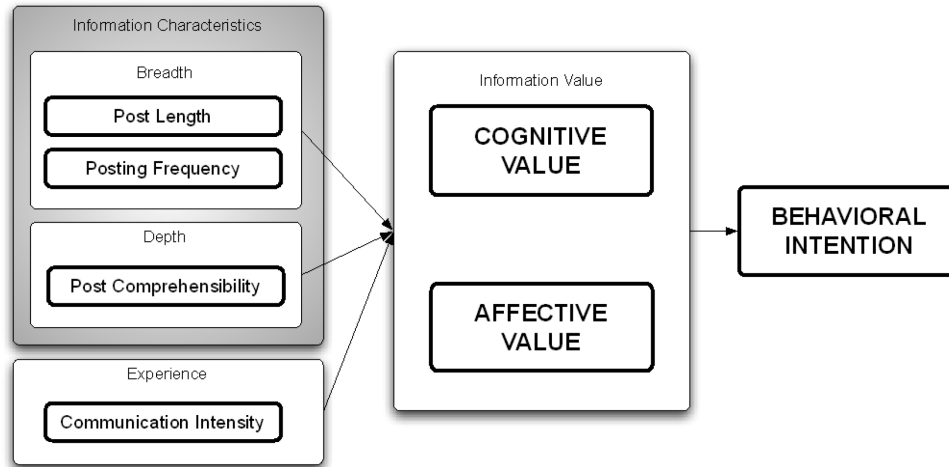


Figure 9 **Research Model B2**

In this model we present a part of the process of information evaluation on SNS. The dependent variable is the intention to engage in certain behaviour on SNS: comment, like, read or ignore the post. It has been numerously proven that a person's intention to perform certain behaviours will be the immediate determinant of actual behaviour (Fishbein and Ajzen 1975). The intention of behaviour is, in turn, determined by the cognitive and affective components of the perceived value of the information that the users receive on SNS. We differentiate between the affective and cognitive components of information value, as affective and cognitive dimensions have been found to distinctly impact behaviour (e.g. Crites et al. 1994). Three main factors impact the two dimensions of value in this model: (i) the breadth of information; (ii) the depth of information; and (iii) the experience of communication with the source of information. We can recognize the elements of the general model presented in figure Figure 4: contextual information which is in the model reflected by the breadth and depth of information as well as the experience of communication with the source of information.

Information Characteristics

When we talk about the information characteristics, we make use of the social construction theory (Berger and Luckmann 1966). It postulates that the meaning of information is socially constructed, that is intertwined with the social setting in which it is encountered (Schutz 1967, Garfinkel 1967). Information sharing on SNS is a written discussion among users, the meaning of which is derived from its context. Therefore, in order to interpret the information that is shared on SNS, one might impose his or her own subjective meaning on it that derives from own experiences (Garfinkel 1967). At the same time, however, one has to understand the context of the person who is sharing the information. Social presence theory (see section A1.3), implicitly assumes that the presence of the sender influences the recipients understand-

ding of the messages. Therefore, in order to be able to understand the other person better, contextual cues about the information as well as about the person who is sharing the information are important. Hereby we differentiate between cues that promote the depth and the breadth of information. As our analysis is centred around a single post shared by someone in the network (the source), we define the breadth of information as the length of the post as well as the frequency of posting of the source of the information. At the same time the depth of information refers to the comprehensibility of the shared piece of information. As breadth is exacerbated by the frequency of posting of a particular person, depth can be stimulated by the increased frequency of communication.

Breadth of information has two dimensions: on the one hand, the length of each single post, and the other hand, the total number of posts that are exchanged on the network. As on SNS over 30 billion pieces of content are shared each month (Facebook 2011a), we approximate this measure by the amount and frequency of posting of the person from whom the information is coming. Due to their fundamental differences in the underlying qualities, these two measures of breadth will have different impact on the resulting information value.

The length of a post – measured by the number of words – is the information input that users have to process in order to evaluate the presented information. Scholars across disciplines have found that performance of individuals, e.g. quality of decisions or reasoning in general, positively correlates with the amount of information (Eppler and Mengis 2004, Miranda and Saunders 2003). In line with these findings, we expect increasing length of the post to enhance the perceived value of the post. However, increases of information input after a certain level may result in information overload (Schneider 1967). In fact, the relationship between the amount of information and the quality of decisions possesses an empirically verified u-shape form (Schneider 1987): after a certain limit the additional information ceases to have a positive impact on performance and reasoning of individuals. However, using our main methodology we can not model a u-shape relationship with the value of information, and therefore hypothesize:

B2.1: *The length of the post is positively related to the affective (H1a) and cognitive (H1b) value of information on SNS.*

Our second measure of breadth is the posting frequency of the source of information. Postings from the same person on the network increase the breadth of information shared by that person and with it – all the information that is shared on the network. If we look at the distribution of the posting frequency presented in table Table 12, we notice that people perceive that the majority of their friends on the network post sometimes or even more often. Our qualitative study reveals that as the networks of users grow, there is increasing probability to have several “spammers” on the network: “*Every second message is from Sam and most of them are not useful to me*”. As people feel overloaded by such information, they might evaluate information from these people negatively.

The concept of information overload has been explored especially in relation to new media. Simultaneity maximizes “floor time” available to each individual and thus increases the number of ideas conveyed in a group discussion (Thorngate 1997). Especially media low on social presence (such as e-mail) have been

found to increase the breadth of communication, and by impeding reciprocity result in information overload (Miranda and Saunders 2003). Individuals cope with potential overload by being selective about the information to which they attend and are unlikely to attend to information when overloaded (Schultz and Vandebosch 1998). Therefore, the increasing amount of information coming from the same person might cause information overload and lead users to ignore this information. Thus, increased posting frequency from one person by making it unable to attend to each piece of information, may negatively impact the value of information from this person. In support of this proposition, high frequency of posting in online chats requires quicker and more sustained processing by group members and can cause information overload (Jones et al. 2008). Therefore we hypothesize that:

B2.2: *The posting frequency of the source of information is negatively related to the affective (2a) and cognitive (2b) dimensions of attitude towards the post.*

Depth of information is approximated by the comprehensibility of information and by the shared meaning that the two parties – the user who evaluates and the source of information derive from it. Information possesses different meanings for different people, based on their backgrounds and positions in a social setting (Schutz 1967). Understanding thus emerges from shared human experiences (Schutz 1967). Thus, it is not only the language of the information that has to be understood, but also the meaning of it, which is socially constructed. Already in the qualitative study we find evidence that in order to evaluate information, users have to understand the context in which information was created: “*And I don’t like it, because I do not know what she is talking about: ‘I feel like I never left’, left what, who, when?*”. If users do not share the meaning of certain information with its source, they might negatively evaluate it.

Interpretation of information is necessary for favorable decision outcomes. In other words, information has to have a certain meaning be used for decision making (Miranda and Saunders 2003). If people share meaning of the information, they are better able to interpret it and devise more complex solutions based on it (Miranda and Saunders 2003). Media low on social presence (such as e-mail) have a negative impact on the depth of information shared, as by enabling only written communication, they impede reciprocity and thus make it difficult to respond to a comment immediately after it is made. Therefore On SNS, people are more likely to respond to simpler messages in the “overloaded mass interaction” in online forums (Jones et al. 2004). We therefore hypothesize:

B2.3: *Comprehensibility is positively related to the affective (H3a) and cognitive (H3b) value of information.*

Experience of Communication

Talking about experience of communication with a certain communication partner, we use the principles the Channel Expansion Theory (Carlson and Zmud 1999) elaborated upon in section A2.3. This theory postulates that the experience of communication with someone leads to the accumulation of knowledge of what this person knows and which capabilities possesses, and thus users might extract more value in communicating with this person on the network. People use information generating strategies as well as ongoing communication to acquire knowledge about others (Walther 1992). On SNS, people can gather

the information about the other person by going to the profile or following the news, as well as by exploiting the possible ways of communication either publicly (by posting something on their profile, commenting or rating the information) or privately (by sending private messages or chatting). Therefore, the more people communicate with the source of the information, the more information they will acquire about that person. This information might be used in several ways.

On the one hand, communication intensity can be used as a proxy for the level of tie strength with the source of information, as users tend to communicate more with those they are close with. In line with the information processing theory (Ajzen and Sexton 1999), communication intensity can thus act as a cognitive heuristic and positively impact information value. Communication intensity has been recognized as important for determining information relevance on Facebook (Kincaid 2010). Alternatively, communication intensity helps to construct the shared meaning of information between the two people. Shared meaning results from everyday interaction (Garfinkel 1967). The more people communicate with someone, the better they are at encoding the information from that person, using cues relevant to him or her, supplementing them with contextual information and thus processing information from that person more efficiently. Therefore, the more people communicate on SNS with someone, the higher is the chance that they will understand the context surrounding the information that this person is sharing and therefore this information will have more value for them. We hypothesize:

B2.4: *Communication intensity with the source of information is positively related to the affective (H4a) and cognitive (H4b) value of information from that source.*

Behavioral Intention

Moreover, we want to explore how cognitive and affective value of information impacts the behavioral intention, and the subsequent behavior of users on SNS. TRA postulates that users act with respect to their intentions, which, in turn, are influenced by attitudes and subjective norms (Fishbein and Ajzen 1975). Technology Acceptance Model (TAM)—tailored specifically to evaluate adoption of IT—explores the impact of perceived usefulness and ease of use on user attitudes and the subsequent intention to use a specific technology (Davis 1989). The model is applied in a wide array of studies in IS (Hu et al. 1999), and focuses on attitude as the main determinant of system use. In line with these models, we presume that the affective and cognitive value of information will impact the intention to do something with the post (such as read, like or comment), translate into real behavior.

In different contexts affective and cognitive dimensions of attitude have been found to perform differently (Crites et al. 1994, Voss et al. 2003). On SNS both attitudes can be distinguished. On the one hand, SNS are hedonic information systems (Trevino et al. 1990) the usage of which may result in affective value of information. On the other hand, SNS can deliver a lot of valuable information (Ellison et al. 2007) and thus promote the cognitive value. As SNS mainly serve the social and entertainment purpose (Krasnova et al. 2009a), than are the source of instrumental help or useful for performing certain tasks (Constant 1996), affective value that is associated with SNS use will be higher than the cognitive value. Therefore we hypothesize that:

B2.5: *Affective (H5a) and cognitive (H5b) value of information are positively related to the intentions of behavior of users on the Newsfeed, whereas the former value is more salient in the context of SNS.*

Methodological Approach

In this empirical study we also employ methodological triangulation. Our main method involves testing the relationships with a SEM-PLS methodology, but we also check our findings with a Panel GLS model. In this way we make sure that our results are not driven by the employed empirical specification and show that a clear pattern present in the data we collect.

Partial Least Squares (PLS) approach was used to evaluate the proposed model due to its suitability for testing and validating exploratory models (Henseler et al. 2009). The choice of the methodology is further justified by the fact that PLS is mainly used to measure multi-item latent constructs that most of our variables represent. Moreover, as PLS requires fewer statistical assumptions, it can be used even when normality assumptions are violated (Chin 1998), which is the case for most our variables. For SEM-PLS the measurement and then the structural model were evaluated (Chin 1988). For the structural model, convergent and discriminant validity were assessed. For the measurement model, coefficients and their significances were used. All calculations were carried out using SmartPLS 2.0 (Ringle 2005). SmartPLS standardizes all indicators in the first step of the analysis, therefore differences in scale width across different constructs are addressed.

As SEM requires several indicators for the measured constructs, more constructs of the complete survey presented in Appendix 2 were used. Information value was measured multi-dimensionally, affective value was operationalized by the likability and interest level of information. Cognitive value was measured by perceived usefulness and relevance of information. Except for post length which was recorded by the application automatically, all other constructs were measured by several indicators. Comprehensibility had two dimensions: meaning and language of the post. Posting was measured based on the perceived frequency and perceived amount of information that the source posts. Communication intensity was measured by the frequency of public and private communication as well as passive following. For all of these items, only reflective measurement evaluations were used in the SEM model.

As a double-check of our findings, we use a Panel GLS specification with random effects. We construct a linear model of the information value derived from a post. The latent variable representing this information value comprised three components: (1) the post-specific characteristics, (2) respondent-specific characteristics, and (3) a random disturbance term (similar to the model B1 in section 3.4). As we have to build averages from the indicators of information value to be able to replicate the findings from the SEM-PLS model, we can not use Ordered Probit specification. Our method involves assuming the existence of the latent variable y^* , and then estimating an GLS specification, directly on the respondent's cognitive and affective post evaluations, while controlling for the respondent-specific influence, ξ , via the inclusion of user-specific random effects (Butler and Moffitt 1982). In the robustness check as opposed to the SEM-PLS we can control for the respondent-specific effects, as each respondent evaluated up to 6 posts and the evaluations might be driven by some respondent-specific, rather than post-specific characteristic.

As the panel regression methodology requires a balanced sample to control for the respondent-specific effects, we have to reduce the sample to 810 observations as in model 1.

Estimation Results

For SEM-PLS, first the measurement and then the structural model were assessed. To examine validity of the measurement model, convergent and discriminant validity were assessed. The results are presented in Table 14. For convergent validity, three criteria have to be fulfilled. First, indicator reliability is ensured, if all factor loadings are higher than the required cut-off criteria of 0.7 (Hulland 1999), which is the case for all indicators in our model. Second, composite reliability of all our latent constructs is above 0.8, which exceeds the minimum required threshold of 0.6 (Homburg et al. 1995). Third, Average Variance Extracted (AVE) of all latent variables in the model is bigger than 0.5 (Fornell and Larcker 1981). Taken together, convergent validity can be assumed. As the length of the post and behavioral intention were measured only by one indicator per construct, their AVE's are equal to 1, and thus no evaluation of the above criteria was performed for these variables.

Table 14 Convergent Validity of Constructs in Model B2

Construct	Indicator	Factor Loading	AVE	Composite Reliability	Cronbach's Alpha
Affective value	likeability	0.945	.89	.94	.88
	interest	0.946			
Cognitive value	usefulness	0.955	.91	.95	.91
	relevance	0.963			
Communication Intensity	private	0.835	.70	.90	.86
	public	0.902			
	following	0.885			
Posting	frequency	0.794	.80	.88	.81
	amount	0.988			
Comprehensibility	language	0.943	.81	.89	.78
	meaning	0.860			

Second, discriminant validity, indicating the degree of difference between constructs, was assessed by ensuring that the square root of the AVE for any latent variable is bigger than the correlation between this variable with all other latent variables in the model (Fornell and Larcker 1981). The results presented in Table 15 reveal that in the tested model no correlation between two variables was bigger than the square root of the AVE. Hence, discriminant validity can be assumed. We note that the correlations between the affective and cognitive dimensions of information value as well as the behavioral intention are quite high (0.65-0.75), although discriminant validity of our latent variables is assured. This leads us to conclude

that although the dimensions of attitude are highly correlated, they can be empirically distinguished, supporting the findings of Ajzen and Sexton (1999).

Table 15 **Discriminant Validity of Constructs in Model B2**

Construct	AFF	COG	C	BI	L	P	Co
AFF: Affective (AFF)	<i>0.943</i>						
COG: Cognitive (COG)	0.749	<i>0.954</i>					
C: Communication Intensity	0.418	0.378	<i>0.837</i>				
BI: Behavioural Intention	0.744	0.657	0.492	<i>1.0</i>			
L: Length	0.048	0.075	-0.017	0.073	<i>1.0</i>		
P: Posting frequency	0.147	0.152	0.418	0.203	0.037	<i>0.894</i>	
Co: Comprehensibility	0.362	0.318	0.165	0.343	0.021	0.107	<i>0.9</i>

At the next step significance of the path coefficients was evaluated. PLS does not make any assumptions on the distributions of the latent variables, which makes standard parametric testing impossible. Instead, t-tests are performed on the basis of bootstrapping results (final bootstrap was performed with 200 samples and cases equal to the sample size – 857). The first two columns of Table 16 represent path coefficients and respective significance levels for the impact of the explored informational characteristics and experience factors on the cognitive and affective dimensions of value of information.

First of all, post length is associated positively with the cognitive (0.077**) and also marginally with affective (0.051*) dimensions of value. Therefore we support the hypotheses B2.1a and B2.1b. Second, posting frequency exerts a marginally significant negative impact only on the affective value (-0.050*), and does not have any impact on the cognitive value. Thus, we find mild support for the hypothesis B2.2a and have to reject hypothesis B2.2b. Comprehensibility of the post is positively and significantly associated with both affective (0.303***) and cognitive (0.262***) dimensions of information value. Therefore we support hypothesis B2.3. At the same time, communication intensity has a positive correlation with affective (0.390***) and (0.346***) with the affective and cognitive dimensions of value, respectively, thus supporting hypothesis B2.4. By the absolute value of the coefficients we notice that communication intensity and comprehensibility of the post are particularly salient in predicting both affective and cognitive information value. Moreover, the impact of communication intensity on both the affective and cognitive components of attitude is higher than that of comprehensibility of the post (the corresponding t-test yielded a test statistic of 2.02 with affective and 1.97 with cognitive attitude).

The results of the robustness check via a Panel GLS model presented in the last two columns of Table 16 reproduce most of the results obtained with SEM-PLS. The only exception is the insignificant impact of the posting frequency also on the affective value of information. All the other variables: post length, comprehensibility and communication intensity are positively associated with affective and cognitive dimensions of information value. At the same time, the coefficient of communication intensity appears to be the highest, indicating that this factor mainly determines information value on SNS. As posting frequency in

the basic specification was significant only at the 10% level, and all other effects of the SEM-PLS model coincide with the Panel GLS, we conclude that our findings were not driven by the estimation method.

Table 16 **Estimation Results of Model B2 (information value)¹¹**

Variable	Structural Model (SEM-PLS)		Panel GLS (random effects)	
	Affective	Cognitive	Affective	Cognitive
<i>Post Length</i>	0.051 *	0.077 **	0.005 *	0.007 **
<i>Posting Frequency</i>	-0.05 *	-0.024	-0.093	-0.115
<i>Comprehensibility</i>	0.303 ***	0.262 ***	0.471 ***	0.466 ***
<i>Communication Intensity</i>	0.390 ***	0.346 ***	1.21 ***	1.18 ***
<i>Constant</i>	-	-	2.37 ***	0.785
<i>R²</i>	0.268	0.217	0.22	0.18
<i>N</i>	857	857	810	810

The results of the impact of the affective and cognitive dimensions of information value on the behavioral intention with respect to the post are presented in Table 17. We find that both affective (0.574***) and cognitive (0.228***) dimensions of value significantly impact the behavioural intention towards the post. Thus, we confirm the hypotheses B2.5a and B2.5b. Additionally, affective attitude is a stronger predictor of the behavioural intention than cognitive: the corresponding t-test yields a test statistic of 6.5. These results are also reproduced if we conduct the evaluation using the panel GLS model, and therefore we conclude that affective value indeed plays a more important role for the behavioral intention.

Since PLS does not generate an overall goodness of fit index, model validity is assessed by examining the structural paths and R^2 values. R^2 measures the share of the variance of the latent endogenous variable, which is explained by the latent exogenous variables in the model. For the purposes of explorative research, R^2 is considered high when it is above 0.65, R^2 of over .33 is considered sufficient, and R^2 of over .19 is also accepted (Hansman and Ringle 2005). The R^2 of the affective and cognitive dimensions of information value are 0.268 and 0.217 respectively, which are acceptable considering the few exogenous variables that predict them as well as the exploratory nature of our research. The explored variables – contextual information and experience in communication with the source of information – are better at predicting the affective than the cognitive information value. R^2 of the behavioral intention model of 0.577 is close to the high benchmark, suggesting that two dimensions of attitude do indeed explain a large

¹¹ - ***p < 0.01; **p < 0.05; *p < 0.10

share or variance in the behavioral intention as suggested by previous studies (Hu et al. 1999, Ajzen 2005). We note that the R^2 of all models obtained using the panel GLS specification offer similar values.

Table 17 Estimation Results of Model B2 (behavioral intention)¹¹

Variable	Behavioral Intention	
	SEM-PLS	Panel GLS
<i>Affective Value</i>	0.574 ***	0.317 **
<i>Cognitive Value</i>	0.228 ***	0.108 ***
<i>Constant</i>	-	1.17 ***
R^2	0.577	0.59
N	857	810

Discussion

This paper provides an array of theoretical contributions about the relationships of the explored contextual and experience factors on the two dimensions of value. First of all, we find that the depth of information and the experience of communicating with the source of information are more important than the breadth of information shared in determining information value. In contrast to previous studies (Jones et al. 2008) which link the dimensions of the breadth of information - length of post or the posting frequency of users - to information overload, these variables exert only a slight impact on information value in our study. In our study, posting frequency, although it promotes the breadth of interaction, only has a slight and non-robust impact on the affective value of information. Length of post is positively perceived by the users for the evaluation of information.

These findings show that the breadth of information does not impact value of information negatively, as some theoretical propositions have suggested. First, new media such as SNS were accused of the lack of contextual cues that provide for the sense of presence of other people during the interaction and therefore impede reciprocity of the information shared (Miranda and Saunders 2003). Second, increased sharing due to simultaneity of information exchange tends to result in information overload (Schultz and Vandebosch 1998), and thus the increase in breadth of information sharing will negatively impact information value. This is probably due to the fact that SNS as communication medium is able to filter out the unnecessary information as well as provide users with enough contextual information to be able to perceive others' presence and respond to their messages if needed.

Moreover, we find that the depth of information has a significant and positive impact on the value of information, exemplified by the comprehensibility of information. This finding supports the theory of the social construction of meaning proposed by Miranda and Saunders (2003): users have to understand and

interpret information in order to get value from it. What we show in this study that shared meaning is created based on the language as well as contextual information that the post contains.

The most interesting finding of the study is that the experience of communication with the source of information is the most salient factor in determining perceptions of value, overriding the impact of comprehensibility of the post. It appears that unclear posts from people with whom one communicates a lot are perceived as more likable and useful than clear posts from people who one rarely communicates with. This might be explained in several ways. On the one hand, this hints at the heuristic processing of information by users: communication intensity serves as a heuristic that increases the value of the post, notwithstanding the shared meaning. On the other hand, this might support the findings of Carlson and Zmud (1999) who argue that the richness of the medium depends on the level of experience with it. Therefore, communication intensity is the most important prerequisite of information value: if people do not communicate with each other, they find it difficult to interpret information from each other and therefore such information does not possess value for them. The more people communicate, they develop a shared meaning and understanding and thus can process information quickly and efficiently, increasing its overall value.

Another important contribution of our study is that it is rather the affective than the cognitive information value that determines the behavioural intention of users with respect to the post. That is, users are more prone to comment and like the posts that are funny and interesting, rather than useful, thus corroborating the hedonic function of SNS recognized in previous studies. There is also a slight difference in the impact of the explored factors on these two dimensions of value: posting frequency has an impact only on the affective evaluations, whereas post length is more important for the cognitive information value. This is quite intuitive, as high posting frequency can easily serve as a source of irritation, especially by people with whom a user does not communicate a lot, whereas post length is necessary to evaluate the usefulness of information. We note the necessity to differentiate between these two components of information value in further studies.

4 Algorithm Design and Evaluation

As we have seen from the studies presented above, information overload is an acute problem for SNS users. As users increase their networks and as the frequency of usage of the network increases, the amount of information exchanged on the network increases manifold and users have to apply certain strategies to cope with it. The findings of the qualitative study presented in section 2.4 suggest that users can fight information overload by hiding posts from people they are less interested in or cleaning up their networks. However, users rarely utilize these strategies as they are bounded by time constraints, social pressure and other psychological distortions. Therefore, users tend to mainly rely on the heuristic processing of information as their main strategy. Therefore in the empirical studies presented in section 3 of this chapter we aimed to identify which heuristic cues have a significant impact on information value. We can use the findings of these studies to design information filtering algorithms for the users. In this

part of the dissertation, we design and evaluate several algorithms that filter and ranks information on SNS. Hereby this study taps into the platform side of the theoretical model presented in Table 2. We present the theoretical background and the set-up of the algorithm that recommends content to users in the next stage.

4.1 Theoretical Background

Recommending content to users has always been an important task of the information systems, which requires both filtering and ranking of information. Several approaches to information filtering exist: i) *collaborative filtering* based on the similarity of preferences between users widely used in e-commerce to recommend products (Konstan et al. 1997); ii) *content relevance* approach matching the topic interests of the user and the content vector of presented information used to suggest news items (Pazzani et al. 1996); iii) *social voting* based on the frequency of mentioning or rating of information by other users (Hill and Terveen 1996); and iv) *social matching* system that recommends people to each other on SNS (Chen et al. 2011).

Useful insights for the design of filtering algorithms are provided in the studies on microblogging applications such as Twitter, where the problem of information overload is even more acute than on SNS as the average frequency of posting is even higher (Chen et al. 2010). The best performing algorithm which selects posts from the outer circle of followees (as opposed to direct followees) and ranks them by both content relevance and social voting achieves an accuracy¹² of ca. 72% (Chen et al. 2009b). In the follow-up study, authors extend the input factors to account for thread length and tie strength which further improve the accuracy of the algorithm (Chen et al. 2010).

Similar efforts have been taken to recommend information on SNS, such as Facebook. A social matching system developed for SNS to recommend friends to each other uses the available social network information and matching of user-generated content (Chen et al., 2011). The easiest heuristic is to recommend friends of friends, however more complicated systems are usually employed to decide which friends to recommend first. To predict the importance of the information on the Newsfeed, Paek et al. (2010) use Support Vector Machine (SVM) algorithm and use all possible factors as input (in total over 50), including communication and post characteristics, message text and corpus features, as well as shared background information (Paek et al. 2010). In a binary classification the highest prediction accuracy of the algorithm lies at 69.7%. The most important factors are tie strength with a friend (implied using a myriad of indicators) and content relevance (matched using topic vectors): if any of these factors is not considered, classification accuracy drops to 63%.

In contrast to presented studies, we assume that already with fewer factors than those used by Paek et al. (2010) a satisfactory level of prediction accuracy can be achieved. Therefore, the insights of the two empirical studies presented above provide the solid theoretical foundation on whether to include certain

¹² - Classification accuracy measures the frequency with which the algorithm correctly classifies an item.

factors into the algorithm or not. To our knowledge, no study so far has conceptualized the inclusion of factors into a filtering algorithm, but simply used all data. Although social network data is usually available on the network, this results in large amounts of data to process for the algorithm which may reduce its efficiency, especially if an on-line ranking system is implemented for SNS. Our first research question is: *What level of filtering accuracy of the information on SNS can be achieved using the factors that significantly impact information value?*

Moreover, previous authors have implemented binary classifications as a type of a spam filter, but the recent developments show that filtering out the irrelevant posts does not solve the problem of information overload. Therefore our goal is not only to filter the posts, but also to rank the posts for the user in order of their relevance. Ranking of posts allows users to determine which amount of information they want to process themselves, and thus reduces the feelings of information overload. Ranking requires a finer-grained classification of posts into classes of relevance, which is only possible if a moderate amount of data is used (Paek et al. 2010). Our second research question is: *Which ranking accuracy of the information on SNS can be achieved?*

Studies confirm the importance of tie strength in determining the relevance of the information on SNS (Morris et al. 2010). However, the information about the underlying tie strength is not available on the network and can only be inferred. Gilbert and Karahalios (2009) gather an extensive amount of social network data, including such complex characteristics as inbox thread depth or the frequency of positive and negative words exchanged between users, in order to distinguish between strong and weak ties on Facebook, achieving an accuracy of over 85%. Aiming to reduce the amount of data used, the third research question is: *What information available on SNS is a better predictor of tie strength between users?*

4.2 Input Factors

For our filtering and ranking algorithm we mainly use the insights from the empirical studies presented above. We want to predict two dimensions of information value that we explore in both studies – cognitive and affective. We want to explore which factors pertaining to information on SNS impact these dimensions of information value. The factors can either characterize the *information* exchanged, such as the number of ratings and comments it received, or characteristics of the *relationship* with the user who shared the information. Moreover, these factors can be *objective*, the same for all the "receivers" of information, (e.g. post type or word count), as well as *subjective*, unique to a particular relationship between the "sender" and the "receiver" of information (e.g. understandability or similarity of interests). We differentiate between the objective and subjective factors as the factors that are objective can be used straightforwardly by the algorithm, whereas to evaluate subjective factors, explicit user evaluations are needed. However, all of the subjective factors we use for the algorithm can be measured objectively using the available network data: communication intensity and posting frequency can be collected and analysed, whereas comprehensibility can be implied, for example, by the match in languages reflected in the profile.

We justify the inclusion of the variables into the algorithm using the insights from the two empirical studies presented above (cf. Table 13 and Table 16), which are summarized in Table 18. More specifically, the first study delivers valuable insights on the impact of social information on the dimensions of information value: ratings impact both dimensions, whereas comments only negatively impact the cognitive information value. The second study provides insights for the other factors: post length, comprehensibility and communication intensity positively impact both dimensions of value, whereas posting is only significant for the affective value.

Table 18 **Algorithm Input Factors**

Factor	Operationalization	Affective Value	Cognitive Value	Combined	Justification for inclusion
Objective Factors:					
Post length	number of words	x	x	x	B2
Social Information	number of “likes”	x	x	x	B1
	number of comments		x	x	
Post Type	photo, link or status	x	x	x	B1 + extra
Subjective Factors:					
Post Comprehensibility	language				B2 + extra
	meaning	x	x	x	
Communication Intensity	public		x	x	B2 + extra
	private	x		x	
	following	x	x	x	
Posting Frequency	frequency	x	x	x	B 2 + extra
	amount				
Similarity	match in tastes	x	x	x	extra

Mainly subjective *relationship characteristics* concern the underlying tie strength between the “poster” and the “receiver” of information. In fact, the results of study 1 show that users prefer information from their strong rather than weak ties on SNS, although weak ties are known to possess more potential in these environments (boyd and Ellisson 2008). Tie strength, however, is not reported by the platform and can only be implied using the information available on the platform (Gilbert and Karahalios 2009). First, *similarity* can serve as a good indicator of tie strength, as users tend to have similar interests with those they are close with. Shared interests or shared background information are often used to filter information on social applications (Paek et al. 2010). Second, *communication intensity*, reflected in public and private communication as well as passive following, positively impacts information value on SNS (Koroleva et

al. 2011a) and has been used to imply tie strength (Paek et al. 2010). We already explored the impact of communication intensity in study 2, however here we want to differentiate between different types of communication in their impact on information value. The new factor we include into the analysis in this study is similarity of interests between users. In order to determine a finer grained impact of the explored variables on information value as well as explore the impact of newly included variable (similarity), we carry out a regression analysis of the variables we are considering to include into the algorithm on the dimensions of information value. We are conducting this analysis in order to limit the number of factors we include into the algorithm so as to increase its performance and efficiency.

As users evaluated information on an ordinal scale, we estimate an Ordered Probit regression (Greene 2000) tailored to use with the dependent variables of this type. Moreover, as each respondent evaluated six different posts, we apply a panel-data specification via the inclusion of user-specific random effects (Buttler and Moffitt 1982). The results of the regression analysis including this factor in Appendix 4 reveal that similarity has a positive impact on both affective and cognitive information value. We find that also posts of type link is perceived significantly better than status updates for cognitive evaluations, therefore we use post type to predict both dimensions of information value. Our regression analysis also delivers more fine results on the impact of communication intensity, comprehensibility and posting frequency than that achieved with the aggregate results of study 2. First of all, only the meaning of the post has a significant impact on both cognitive and affective evaluations, whereas the language does not have any impact at all. Second, it is rather the frequency of posting than the amount of information that is posted by others that causes negative reactions. Third, what concerns communication intensity, we find that public communication is not associated with affective information value, whereas private communication does not determine the cognitive value of information. In the next step we include only those factors that proved important in determining the respective dimension of information value into the ranking and filtering algorithms. Moreover, we explore whether tie strength can be better predicted by communication intensity or similarity of interests between users based on our algorithm.

4.3 Methodological Approach

In order to filter and rank the information, we use Neural Networks (NN). NN is a well known method that has been successfully applied to real-world classification problems, similar to information classification on SNS. NN are flexible and robust, which is important when classifying noisy data we are dealing with: either the subjective information provided in surveys or objectively obtained from Facebook. NN allow us not only to do an effective binary classification, but also to classify posts into 3 and 6 classes. As the number of classes increases, it is possible to obtain a more “fine grained” ranking, although the accuracy of the classification is expected to decrease. At the same time, the classification mistakes tend to be less severe (for example, ranking the post as “very useful”, when it is, in fact, “slightly useful”), compared to the failure of an accurate binary yes-no classification. Moreover, a fine-grained classification is a first step in the direction of post ranking – which is a more challenging, yet the final goal of classification systems. Therefore we set out to design both: a filtering and a ranking algorithm for SNS.

Table 19 Possible Algorithm Designs

Input Factors	objective	all: objective + subjective	
Target Variable	affective value	cognitive value	
Number of classes	2 classes	3 classes	6 classes

For the design of the filtering algorithm, three design dimensions are taken into account (cf Table 19): the combinations of input factors (2), the different target variables (2) and the different number of classes (3), resulting in total of 12 algorithms. Specifically, the experiments were run with two combinations of input variables: one considering only the objective factors, and the other with all the factors, including subjective. Only the significant input factors identified in the studies presented in Table 18 were included into the algorithm to predict the two dimensions of information value: cognitive and affective. The algorithm predicts different number of classes of information value, where two classes were obtained by merging the corresponding positive and negative categories of the information value constructs, three classes – by merging the following categories: very (-) and quite (-), slightly (-) and slightly (+), quite (+) and very (+) (for the full scale, please refer to Appendix 2).

For the classification, the FeedForward network provided by the Neural Network Toolbox in Matlab was used (Demuth and Beale 1997). After several tests, the best results were obtained with the following configuration of the network: one hidden layer with ten neurons; a log-sigmoid transfer function for the hidden layer; a linear transfer function for the output layer; a gradient descent with momentum weight and bias learning function; the Levenberg-Marquardt back propagation function for training the network. For classification, the 929 posts were divided into three sets: training (559 posts), validation (185 posts) and testing (185 posts). The selection of the posts for each set, as well as the initialization of the network weights is random. Thus, the performance of the network depends on the random seed and varies from one execution to another. Therefore, the reported accuracy of the network classification corresponds to the average value of 100 independent runs.

4.4 Computational Results

Filtering Algorithm

We use the classification accuracy metric as well as the mean standard error to compare each of the 12 implemented algorithms. The algorithms are compared based on: the different degrees (classes) of importance (2, 3 or 6 classes), for each of the target variables (affective and cognitive information value), as well as when using only the objective vs. all input factors. Classification accuracy measures the frequency with which a recommender system correctly classifies an item (Herlocker et al., 2004) and thus can be considered a reliable measure for comparison.

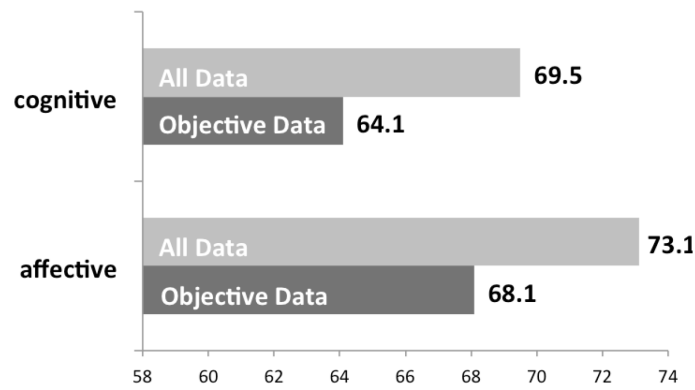


Figure 10 **Classification Accuracy in two classes**

When classifying the posts into two classes (Figure 10), the average relative prediction improvement is 21% compared to a baseline of 50% (completely random classification). The maximum achieved accuracy of the algorithm is 73.1% when predicting affective value using all data, whereas cognitive value is harder to predict. When using only the objective data, the algorithm achieves an average accuracy of 66%. By including subjective data into the algorithm we can achieve an average increase in accuracy of ca. 5% for both dimensions of information value. However, for affective value objective data allows to achieve a similar prediction accuracy (68.1%) as when using all data for the cognitive value (69.5%).



Figure 11 **Classification Accuracy in three classes**

When classifying into three classes (Figure 11), the average relative improvement compared to a random baseline (33.3%), is 23.2%, which is slightly higher than with the two classes classification (21%). The maximum accuracy achieved is 61.2% again with the affective value of information. Cognitive dimension performs much worse in this classification: using only objective data for the affective value (54.9%) we can achieve a better prediction accuracy than when using all data with the cognitive value (51.9%). However, the increase in accuracy when all data is taken into account as opposed to using only objective data is higher for cognitive (11.1%) than the affective dimension (6.3%).

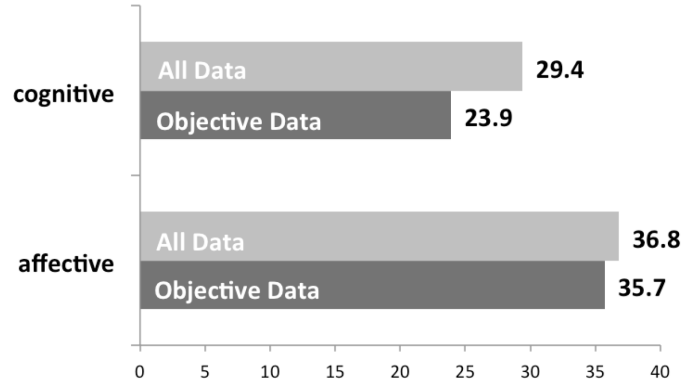


Figure 12 **Classification Accuracy in six classes**

When classifying into six classes (Figure 12) the average improvement is at 17.1% compared against a random baseline (16%), which is lowest compared to other classifications. The highest accuracy of 36.8% is again achieved with affective value when all data is taken into account. Cognitive value performs similar to the classification into three classes: the prediction accuracy when using all data (29.4%) is lower than in case of affective value when using just objective data (35.7%). This occurs due to the fact that objective data is again enough to achieve a comparable level of prediction accuracy (improvement when using all data is less than 1%, whereas for the cognitive value accuracy increases by 5.5% if all data is used).

To further validate our results, we use the Mean Absolute Error metric (Herlocker et al. 2004). MAE measures the average absolute deviation between the predicted classification and the user's classification using equation (1), where p_i is the predicted class and r_i is the users classification, N is the total amount of post predicted by the system. The results presented in table 3 show that the smallest difference between using objective data and all data is achieved for the affective dimension, while the cognitive dimension is the one that benefits the most from using all data. Therefore we can conclude that using objective vs. all data depends on the type of evaluation: to predict affective value of information, using all data is not significantly better than using just the objective data, whereas for instrumental and cognitive evaluations, all data is needed for more accurate predictions.

$$|E| = \frac{\sum_{i=1}^N |p_i - r_i|}{N}$$

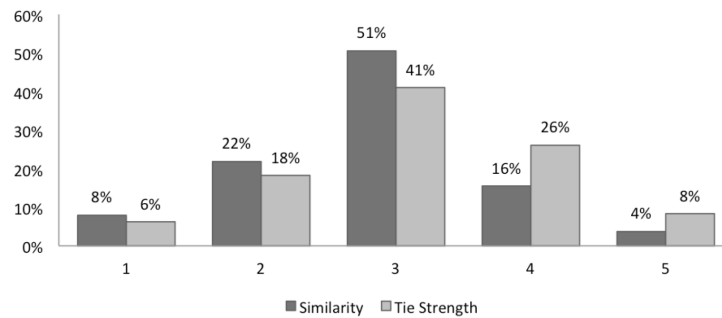
To determine the difference in processing cost when using all data vs. objective data, the time required for the NN to do the classification was measured. The experiment was done with an Intel Core2 Duo CPU at 2.4Ghz and 2Gb RAM. As a result, we observe a clear decrease in processing cost: when using only objective data execution time is on average 316 seconds, whereas when using all data ca. 354 seconds are required. The attained decrease in the necessary processing time for objective data vs. all data is to estimate the value of information is 11.3% for cognitive and 10.1% for affective dimension.

Table 20 Mean Absolute Error Classification Accuracy

Number of Classes	Affective		Cognitive	
	Objective	All Data	Objective	All Data
2 Classes	0.31	0.27	0.36	0.29
3 Classes	0.55	0.44	0.81	0.68
6 Classes	0.89	0.79	1.23	1.08

Predicting Tie Strength

Tie strength is a direct measure of the relationship between the “poster” and the “receiver” of information on SNS. However, in order to quantify the tie strength using the information available on the network, the algorithm would need to process large amounts of data, similar to the model of Gilbert and Karahalios (2009). Therefore we explore whether communication intensity (Kincaid, 2010) or the similarity between users (Gilbert and Karahalios 2009) is a better predictor of tie strength on SNS. By determining which factor better predicts tie strength, we can reduce the necessary processing effort for the algorithm. Already by the distributions depicted in Figure 13 we can see that similarity follows a more normal distribution similar to the one of tie strength: most users have something in common as well as almost as much have very much and nothing in common at all. The skewed distribution of the frequency of communication in Figure 14, however, hints that on average users do not communicate with a majority of their friends, also with the ones they report knowing to some degree. In fact, the correlation coefficient between communication intensity and tie strength is 0.54, whereas with similarity it comprises 0.64.



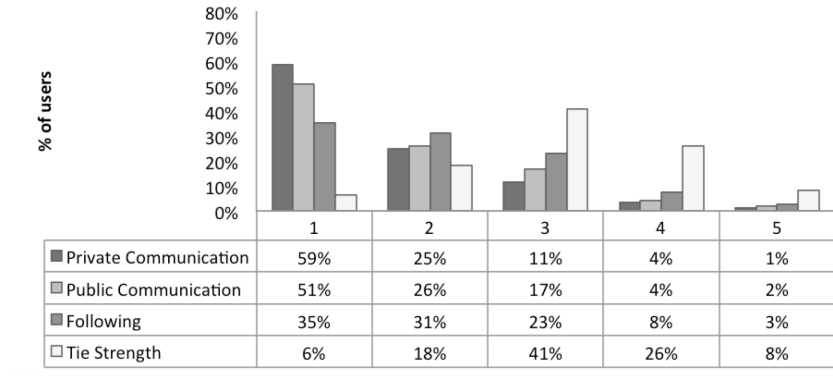
Similarity: 1 nothing in common; 2 hardly; 3 smth; 4 quite; 5 very much in common

Tie strength: 1 do not know at all; 2 hardly; 3 slightly; 4 quite well; 5 know very well

Figure 13 Frequency of Similarity vs. Tie Strength

In order to determine, whether tie strength can be better predicted with similarity or communication intensity, we use NN similar to the way described above. We estimate two algorithms use a neural network (NN) classifier on the whole sample of data: one with three distinct forms of communication intensity and the other with similarity as input factors and tie strength as the target variable in both cases. If we use the

intensity of communication and similarity of interest, the prediction accuracy of the tie strength is 73% and 76% in the binary classification (weak or strong tie) and 44% and 50% in the multiple class one (corresponding to the 5pt ordinal scale), respectively. We conclude that similarity between users is a slightly better predictor of tie strength, than intensity of communication.



Communication Intensity: 1 not at all; 2 rarely; 3 once in a while; 4 regularly; 5 always

Tie strength: 1 not at all; 2 hardly; 3 slightly; 4 quite well; 5 very well

Figure 14 **Frequency of Communication Intensity vs. Tie Strength**

Ranking Algorithm

The neural network algorithm can also be used to rank the posts according to their estimated importance and compare these values with the real ranks provided by users. For the ranking algorithm, we use the average of the two dimensions of information value (affective and cognitive) as the target variable and all factors that have a significant impact on any dimension of value as input (factors indicated in the column “combined” in Table 18). The classification returns a real number which provides a measure of the information value which we use to assign the system’s ranks to the posts for each user. The network was trained using 654 randomly selected posts, whereas the other 275 were used for validation. Once the network was trained, the posts for each user were ranked. On the other hand, in the survey each user evaluated up to six posts which were randomly selected from the Newsfeed. By averaging the evaluations along the two dimensions of information value¹³, we were able to assign a user rank to each piece of shared information and compare these results with the ranks provided by the system. The user ranking and the one obtained from the system are then compared by applying the “precision of preferences” method (Carterette et al. 2008). The accuracy measure provided by this method is the proportion of the pairs correctly ranked by the algorithm. More formally, over all pairs of posts i, j such that i is preferred to j by the user, the “precision of preferences” method returns the proportion for which the system ranked i above j . If two posts have the same user rank the pair is ignored, thus the method is not affected by the presence of posts equally rated by the user.

¹³ - Note that we only take users who evaluated 6 posts, which results in a total of 135 users whose posts could be ranked.

The results of comparing the “real” rankings provided by users with the ones obtained through the algorithm show the ranking accuracy for the target category – information value (that comprises both dimensions of information value) in Figure 15. The average accuracy of the implemented ranking algorithm over the posts of 135 users comprises 74.5%, where the minimal accuracy achieved is 28.6% and the maximum – 100%. The median lies at 78%. The distribution of the ranking accuracy over the posts of the users can be traced in figure 6. We notice a skewed distribution which already signals good performance of the ranking algorithm: for over 70% of the users accuracies of over 70% and higher can be achieved. For almost 30% of the users the prediction errors amount to 20% or less. We consider this a promising result for such a difficult task as ranking of information on SNS.

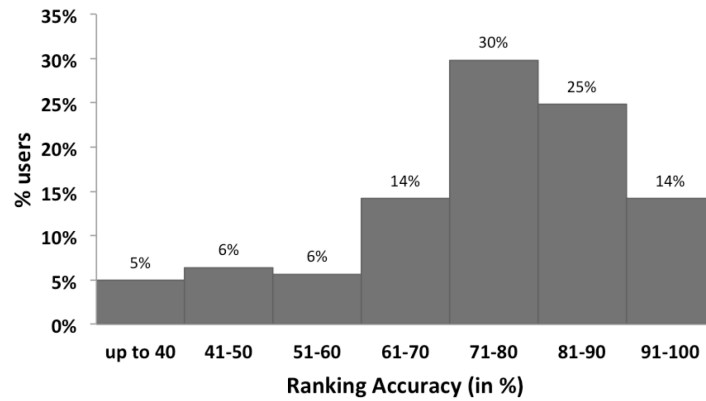


Figure 15 **Distribution of the Ranking Accuracy**

4.5 Discussion

First and foremost, our results confirm that Neural Networks are an effective technique for filtering and ranking information on SNS, which allow to achieve prediction accuracies of up to 73%. One of the main contributions of our work, however, is that it is possible to achieve such prediction accuracy by using much less data than has been done previously. For example, to predict affective value, only the objective characteristics are sufficient, such as number of comments and affirmations, post type and word count. This result underscores the necessity to carefully choose which factors to include into the filtering algorithms. Moreover, we show that using less data increases the efficiency and decreases processing costs of the algorithm: by using only objective data the algorithm performs on average 11% faster, which is especially significant if the classification process has to be done in real time on SNS.

Moreover, our designed algorithm allows to predict different dimensions of information value on SNS. It turns out that affective value of information is much easier to predict than the cognitive value. For most of the predicted algorithms, the accuracy achieved when using just objective data did not improve much when subjective data was added. At the same time, it was similar to or even higher than the accuracy of cognitive value when using all data. This can be best explained by the fact that SNS is mainly used for entertainment and socializing (Krasnova et al. 2010a), and therefore affective value of information is

probably most salient on these networks. Moreover, affective value less depends on the content of the post and can be well determined by the peripheral characteristics of the information. A good example is the rating that the information receives – using the insights from the first empirical study, people are increasingly using the heuristic: “if many people like it, I like it too”. To estimate the cognitive value of information, more complex analyses of the content are needed. For example, here the understandability of information is supposed to play a major role, which as is evident from the results of study 2 is enhanced by increased communication with the person who is sharing the information. As these two are subjective factors, they need to be included into the algorithm for more accurate predictions.

We also find that similarity of interests is a better predictor of tie strength than communication intensity between users. This can be explained by the fact that users presumably use other means to communicate with their close friends (Vitak et al. 2011). This has important implications for network providers, as current algorithms use communication intensity between users as proxy for tie strength. Similarity of users can be approximated by the available network data: the pages the users like, the events they are invited to and the interests they list on their profile.

Furthermore, in our paper we not only filter the irrelevant posts, but also classify posts into multiple classes. This finer-grained classification allows a more precise filtering of the information. Although classifying into two classes allows us to reach higher accuracy, it does not allow us to determine the order of information presentation. If, for example, in case of the two class algorithm the results provide more candidate posts than can be presented to the user at one time, the algorithm is unable to select which ones to present, resulting in an additional loss in the overall accuracy. On the contrary, the multiple classes algorithm would select only the highest ranked posts for presentation.

Finally, we implement an individual ranking algorithm for the users and achieve even higher accuracies than with the filtering algorithm. The ranking is effective, as the amount of posts presented to the user can be adjusted according to different parameters, such as the log-in frequency or be defined by the users themselves, who desire to regain control over information presentation (Tonkelowitz 2011). As no other study until now has attempted a ranking of information on SNS, our results could provide a valuable benchmark for future research.

5 Conclusion

Theoretical Contributions

In this part of the dissertation we have mainly focused on the properties of the information and their impact on the information value users derive from using SNS. We find that different information characteristics have a significant impact on information value. First and foremost, the breadth and depth of information shared have a positive impact on information value. Moreover, we find that users increasingly rely on the opinions of others in their network when they process information. As such, the positive impact of ratings on information value on social applications such as Facebook can be compared to functions of them in recommender systems. At the same time, comments by creating information overload negatively

impact information value. Moreover, experience factors, such as the general frequency of use of the medium as well as specific frequency of communication with specific users increase the value of information.

As users are employing a myriad of heuristic cues presented above, our results show that users process information heuristically on SNS. The most interesting finding is the relationship-primacy effect we observe in the first study: for the strongest ties, any information possesses sufficient value. The weaker is the tie with the source of information, the stronger is the impact of social information – through ratings and comments from other friends – on the value of information. Another reason supporting the heuristic processing of users on SNS lies in the high impact of communication intensity on information value, which overrides such factors as comprehensibility of the post or post length. That is, if people have experience of communicating with others on the network, that is usually enough to evaluate the information from such people highly. At the same time, we find that it is rather the affective, than the cognitive information value that the users derive from SNS.

Methodological Contributions

Methodological contribution stems from the administration of our survey through a Facebook application. From a research standpoint, SNSs and other social media platforms provide substantial benefits in terms of the sheer volume of data available about user activity (Kane and Fichman 2009; Lazer et al. 2009). However, researchers must infer the meaning of some data, and those inferences may or may not be associated with real-world constructs. With our application-based survey, we can capitalize on the strengths but minimize some of the weaknesses of the voluminous data provided by social media platforms. In particular, by obtaining data from the platforms, we can minimize respondent fatigue or respondent inaccuracy. This approach also can ask specific questions that are not captured by existing data, such as “How well do you know this person?” or “How helpful do you find this information?” Other researchers might adopt a similar methodology to expand the number and type of research questions being addressed through SNSs.

Managerial Contributions

Managers are increasingly interested in SNSs as a means to spread information about companies and products. Word of mouth is a far more effective mechanism than any other marketing tool for promoting products and services (Dellarocas 2003). Surveys demonstrate that 77% of surveyed SNS users trust the ratings of their friends more than advertising, and almost 70% have revised purchase preferences after being exposed to negative comments about certain products offered by contacts on SNSs (PWC 2012). Therefore, companies could benefit from marketing products in these networks, though they must be careful about the feedback their products receive. Understanding just how users value and process information on SNSs may provide important implications for social media marketing strategies. For example, our findings suggest that companies can use ratings as direct measure of perceived quality, but they should regard a greater number of comments with caution. The positive impacts of ratings also may have implications for promoting certain ideas, such as arguing for a strategy that releases less information to

cultivate support and thereby bring this limited information to the attention of more users. It also could have implications for how companies monitor SNS platforms to gauge customer sentiment (Gallaughier and Ransbotham 2010). Companies may be best served by focusing on information that either has received a low rating or generated many comments.

Practical Contributions

Furthermore, we provide insights for improving the filtering algorithms used by SNS providers. In our paper we design and implement several algorithms that allow to reduce information overload on SNS. First of all, we show that satisfactory levels of prediction accuracy can be achieved with a subset of available network data by using a NN algorithm. Second, our paper is a first attempt to rank the posts in order of their relevance and thus achieve the highest goal of effective information classification. Our study shows that tie strength is the most important predictor of information value. As tie strength can not be directly estimated with the data available on the platform, we show that it can be best predicted by the similarity of interests between users. Although estimating similarity of interests is not such an easy task, algorithms could use information about shared interests, common friends, common city/work/school of users when predicting tie strength.

Although our findings then suggest that information from strong ties should be preferred, filtering algorithms should also present information from the weak ties in order to provide users with novel content – an important task of recommender systems nowadays (Chen et al., 2010). Hereby rating of the information can be effectively used, which allows to increase the information value from all types of ties, except strongest. Because comments have a negative impact on information value, especially from weak ties, the algorithms should consider this type of social information with care. Alternatively, to avoid a sense of information overload, SNS providers could restrict the number of possible comments or shorten the number of possible symbols available in their comment function.

Moreover, providers should filter the information based on the frequency and duration of SNS use. That is, more active users might be more interested in more detailed information, whereas users who log-in rarely might be irritated by the detailed and frequent information and should be presented with the most relevant information, which is coming from their stronger ties and which has received a high rating.

Limitations

The studies presented in this part of the dissertation are subject to several limitations. Some of these limitations are dealt with in the next part, where we present the results based on the new application and new survey design. Other limitations will be dealt with in the other ongoing or upcoming research projects.

One of the main limitations of the survey design presented in this part of the dissertation (and the studies that are based on it) is that many variables, such as communication intensity or posting frequency, were mainly subjective perceptions of users, which may differ from their behavior on the network. For example, to infer intensity of private communication, such factors as the number of personal messages sent or the number of chats initiated could be retrieved from Facebook instead of asking users about their percep-

tions. Additionally, the experimental environment (by presenting users one post at a time, rather than all the posts on the Newsfeed) might have induced users to process information systematically, rather than heuristically, as well as reduced the perceptions of information overload. Another major difficulty was to measure the ‘intention’ variable on the ordinal scale. Although the elements of this scale – such as commenting or liking – may not have been driven by the same motivations, commenting requires more effort and thus is placed on the higher end of the scale continuum. Thus, in the next step we aim to collect more objective data about the behavior of users on SNS and create an environment in which users process information both heuristically and systematically.

Moreover, our analysis is limited to the evaluation of the impact of social context cues rather than the content of information. This is because on SNS users tend to process information by relying on heuristic cues than systematically evaluating the content. Evaluating content, however, could give additional insight especially into the impact of comments on information value. For example, by adding a dimension of positive vs. negative valence we could better discern whether the negative impact of comments is due to the overload created by the amount of information they transmit or to the controversy of content they convey. Future research could explore the impact of particular content on information value.

The final limitations of our study is the potential selectivity of our sample, which mainly includes young and active Facebook users. We note however that given the continued growing importance of SNS’s in individuals’ daily lives, there is something to be said for studying exactly this group of young and active respondents. Additionally, the fact that most of our data has been collected through friends of the authors, might represent a certain response bias. However, we aim to deal with this bias by extending the sample with other segments of SNS users. For example, one of the off-topic projects not included into this dissertation explores the usage of SNS by teenagers (cf. Appendix 10).

C Network Construction and Network Structure

1 Introduction

In this part of the dissertation we focus on the network structure and network properties, as this is the second source of social capital (cf. Table 2), apart from the content itself. In this part we counterpoise the two types of theory: on the one hand, dynamic theories that concern how networks form, whereas outcome theories concern the benefits that users obtain. So here we set out to explore what are the motivations of users to construct their network and in the second step explore the impact of network structure on the information benefits users obtain.

Social Networking Sites (SNS) per definition enable users to create profiles and link to others (Boyd and Ellison 2008). One of the main affordances of SNS is their ability to provide for forming the relations with a unlimited number of others (cf. Figure 1). Thus, people are able to connect to others that they have known for ages, that they have lost touch with, who they have recently met or even unknown people based, for example, on their common interests. Thus, SNS provide efficient tools to construct and maintain one's network. On Facebook, an average user has 130 friends (Facebook 2011a), although other studies report much higher numbers (e.g. Pempek et al. 2009). As users continue using SNS, their networks tend to grow. However how people construct their networks is still unclear. Do they add anyone they meet in real life? Do they add everyone that sends them a friendship request? As SNS is quite a new phenomenon, there is a lack of existing studies in this domain that focus on motivations of users to construct their networks.

In this part of dissertation we aim to inquire what are the motivations of people behind expanding their networks. Not rarely people are judged by the number and type of friends they maintain, as the known saying goes: tell me who your friend is and I will tell you who you are. Therefore we assume that people will be careful when they are constructing their networks and are guided by specific motivations when they The platform enables two types of network construction behavior: active and passive. Active expanding of the network includes sending a friendship request to someone, whereas passive network formation occurs through accepting of other's requests. These two types of behavior might be motivated by different factors. Sending is regarded as less acceptable than accepting behavior. Not rarely have we heard people denying to be sending friendship requests and only to be accepting ones. This might be due to a response bias, but the question arises: who are those people who do send friendship requests and which factors they are motivated by? Our first research question is:

- *What factors impact the active construction of networks (sending behavior)?*
- *What factors impact the passive construction of networks (accepting)?*

Although in studies presented in previous part of the dissertation we mainly focused on the impact of information characteristics on the dimensions of information value, we have seen that tie strength with the source of the information plays a crucial role in determining the value of information, and that people

process information differently depending on whether it is coming from a strong or a weak tie. Therefore we assume that although social ties are not embedded into the SNS platform, people might be motivated by a different set of factors, depending on the tie strength with the user. As tie strength is a direct measure of network structure on the dyad level (cf. Figure 1), we are interested to know what are the motivations behind expanding the network with ties of different type (strength). Moreover, coming back to the discussion about the definition of SNS as social networking sites, authors report that SNS are mainly used to support existing social relationships rather than form new ones (boyd and Ellison 2008), therefore networking in the definition is misleading. However, SNS encourage people to connect to each other also based on their shared interests and location (thus tapping into supporting proximities between people), not necessarily only based on tie strength. Although majority of users does not add people they do not know, a minority still does (Krasnova et al. 2010c). Therefore our further research question is:

- *Do motivations behind network construction differ between ties of different strength?*

Due to the scarcity of research on the subject of network construction on SNS, we first conduct a qualitative study, where we in a series of interviews with an element of participant observation (in order to ensure real responses from users). In the second step we validate the causal part of the model that links the motivations of users to their sending/accepting behavior (or an intention thereof).

In the next step, we want to explore what is the impact of the constructed network on the benefits users can obtain. Not all users can obtain the same amount and type of informational benefits. Those whose network is more optimally structured may enjoy higher rates of return on their informational demands and obtain more benefits of social capital. However, which configuration of the network confers significantly more informational benefits, is yet to be determined. On the one hand, networks where individuals are tightly interconnected with similar others may provide social support and promote trust, thus enabling efficient exchange of information (Coleman 1988). On the other hand, networks with weaker connections between diverse groups of individuals may provide access to non-redundant information which is not available in their immediate surroundings (Granovetter 1973). SNS allow users to construct and maintain large networks of any configuration they desire, without putting restrictions on the quality of relationship or the frequency of communication (Ellison et al. 2007). In our study we aim to determine which structure of the network brings about more informational benefits to users on SNS.

In the second step, we explore how the formed networks of users impact the value of information users obtain from the network. As opposed to previous efforts which to some extent equated tie strength with network overlap, we want to distinguish the impact of these two dimensions of network structure on information value. On the one hand, as users get to know each other better, their networks start overlapping more. At the same time, as the redundancy of the network increases, information value is supposed to decrease (Burt 1992). In the first part of the dissertation we find, however, that the stronger ties are rather associated with information value. Therefore, we want to shed some light on these inconsistent findings and our next set of research questions can be summarized as follows:

- *Do users prefer information from their strong or weak ties on SNS?*

- *How does network overlap impact the value of information on SNS?*

In order to answer these questions, we develop a Facebook application that simulates the user's Newsfeed and ask users to select the information they would pay attention to. Using the unique capabilities of SNS, we combine two methods of measuring network structure that effectively complement each other: on the one hand, by asking participants to identify the underlying relationships with their friends, and on the other by measuring their network size and relative network overlap. Thus, we are able to combine the subjective evaluations of users with the objective measures of network structure and determine their impact on information value. Using several regression methodologies, we report robust results that show that while strong ties are rather associated with information value, network overlap has a negative impact on the information benefits users derive from SNS.

2 Network Construction Behavior

2.1 Theoretical Background

A multitude of theories (e.g. social exchange theory, theory of the social organization of friendship ties, equity theory, attachment theory) seek to explain how and why friendships and social ties are formed offline. For example, it is suggested that social position plays a significant role in friendship choice (Hallinan 1978/1979; Rainio 1966). Another popular explanation is a principle of social homophily according to which people are more likely to associate with others who are similar to them than with those who are different (McPherson et al. 2001). Overall, most of the existing body of literature focuses on offline friendships. At the same time the analysis of computer-mediated relationships – ‘friending’ - might reveal different dynamics.

Whereas offline friendship is rooted in mutual recognition, sympathy and appreciation (Wright 1978), ‘friends’ in the context of SNSs refer to “all *articulated relationships, regardless of intensity or connection type*” (Boyd 2010, p. 94). A number of studies offer insights into the *structure* of individual social networks online. In these studies existing offline friends are often contrasted with new online acquaintances – ‘strangers’ (Boyd 2010; Pempek et al. 2009; Thelwall 2008). For example, Pempek et al. (2009) find that students are mainly utilizing Facebook to connect to friends that they have a *pre-established offline* relationship with. At the same time, Madge et al. (2009) report that incoming freshmen use SNSs as means of making *new* friends at the university before actually moving there. In this context it becomes crucial to understand the reasoning behind user behavior of adding existing vs. new ‘friends’, since presumably diverging motivating mechanisms are in place here.

Apart from acknowledging that users differentiate between various degrees of tie strength when constructing their networks, existing research offers only mixed and mainly qualitative insights into *why* a particular person is integrated into one's online network. Users may add ‘friends’ for the same trivial reasons as they add others to their address-books: to have an easy access to contact details (Donath and

Boyd 2004). Looking through a socio- psychological lens, Boyd (2010) stresses the importance of such incentives as impression management and self- presentation. Furthermore, users can accumulate social capital by the virtue of being connected to a wider range of people on SNS (Ellison et al. 2007). For example, by communicating with a closely-knit circle of friends a user can gain emotional support, whereas a loose network of ‘weak ties’ may provide useful information and perspectives (Donath and Boyd 2004; Ellison et al. 2007; Granovetter 1973). As a result, expectations about these outcomes may motivate users to expand their networks.

On the other hand, the main impediment to expanding online networks are the privacy concerns of user (Lewis and West 2009). SNS could help expand the networks of user beyond their usual social circle, as the definition of social networking sites suggests. Privacy is one of the main reasons of why people do not add strangers on SNS. However, a single offline encounter is usually enough to promote the necessary trust to initiate an online relationship, which is due to the anonymity and the inability to verify identity online. At the same time reliance on privacy controls may mitigate this privacy-related anxiety and thereby motivate articulation of ‘friendships’ (Boyd 2010).

Beyond individual motivations, platform culture and social norms regarding ‘friending’ underlie individual behavior (Livingstone 2008) and induce users to constantly negotiate “*over what is socially appropriate*” (Boyd 2010, p. 95). Moreover, besides complying with universal social norms present on the platform, which generally favor sending and accepting behaviors, some users may feel pressured to accept a friendship request not to appear rude to the sender (Boyd 2006).

Summarizing, even though previous studies offer a number of insights into the network construction behavior, there are several gaps which need to be addressed. First, existing research offers only scattered insights and no study exists, to the best of our knowledge, investigating the process of network building in a comprehensive way. Second, most findings are too general and reveal no details of the ‘friending’ dynamics. For example, whereas one factor may be particularly relevant in adding a good acquaintance, it may play no role whatsoever when a user has to handle a friendship request from a ‘stranger’. Third, most of the findings are of qualitative nature and hence mainly advance “*conjectures rather than [present] testable evidence*” (Thelwall 2008, p. 1321).

Aiming to address these shortcomings, our study consists of *two parts*. In the *first part*, we use Grounded Theory approach to analyze qualitative data obtained through interviews with Facebook users. As a result of this analysis, a process model of ‘friending’ behavior on Facebook emerges. Building on the qualitative results, in the *second part* we test two causal models which aim to deliver empirically validated insights into individual motivation to: i) accept; and ii) send friendship requests to people with various degrees of tie strength.

2.2 Qualitative Study

Methodological Approach

Taking into account underexplored nature of our research question, we use Grounded Theory methodology to obtain initial insights into the dynamics of the network construction behavior. When using GT approach, data collection goes hand in hand with data analysis (Glaser 1992). For this reason interviews were conducted in two stages. In the first stage, two trained interviewers asked respondents (all students, aged 20-25, 7 male/1 female, different cultural backgrounds) a number of open-ended questions about their behavior with regard to handling friendship requests, for example: *What influences your decision to accept a friendship request?* In order to approximate the interview situation to the real Facebook experience as well as provide ground for discussion, respondents were additionally offered 8 paper-based Facebook profiles of unknown people. Respondents were asked to comment on each profile with regard to the *likelihood* with which they would accept or send a FR to the suggested ‘friend’. These eight interviews of 25 minutes each were analyzed in order to generate preliminary hypotheses as recommended by Glaser (1992).

Insights obtained in stage 1 served as a basis for extended follow-up interviews, which were conducted by 2 authors of this study until *theoretical saturation* was achieved. Eight resulting interviews lasted between 45 and 60 minutes and included elements of observation, as respondents (all students, aged 20-25, 4 male/4 female, different cultural backgrounds) were asked to login to their Facebook accounts and perform their usual actions while the interviewer was asking questions regarding their actions and experiences. For example, once a respondent entered her contact list, she was asked to comment on the structure of her network. This reduced possible deviations related to distorted recall of one’s behavior. In order to ensure that a respondent naturally starts commenting on her behavior regarding friendship requests, each respondent was sent 2 friendship requests as arranged by the authors: one request was from a person the respondent was likely to see in college, but did not personally know (often mutual friends were present) and the other one was from an unknown person. All interviews were video-recorded, transcribed and analyzed using a specialized software atlas.ti 6.1.1.

We pursue the ‘Straussian’ line of GT which allows for prior knowledge of the phenomenon in question as well as formulation of the research question, requires absence of an a-priori theory and uses a paradigm model (Matavire and Brown 2008; Seidel and Recker 2009; Strauss and Corbin 1998). In their approach Strauss and Corbin (1990; 1998) differentiate between 3 stages of data analysis: *open, axial and selective coding*. The process of *open coding* involves identification of initial concepts by looking for patterns in the data through the process of constant comparison (Strauss and Corbin 1998). The following quotation provides an example of an open coding in our study: *“I think, it is good to stay in contact (staying in contact). It is just for convenience (convenience of social interaction) ...and it might even somehow help to substitute things like couch surfing (getting accommodation)...” (Q)*. In the next step, multiple concepts identified during open coding were combined into higher-level categories. For example, the category “Peer Pressure” united the following codes: *“don’t want to offend”*, *“feeling of an obligation”*, *“feeling*

guilty", "*being nice*", "*don't want to be rude*".

The next stage of our analysis – *axial coding* – was dedicated to grouping the categories into families and uncovering the relationships between resulting categories and subcategories at their respective dimensional levels. The coding paradigm by Strauss and Corbin (1998) helped to identify emerging relationships and served as the basis for our conceptual framework. Examples of axial coding will be provided throughout the study. In the following stage of *selective coding* we systematically related a core category - our phenomenon 'handling *friendship request*' - to other categories as well as condensed several categories to bring concepts to a higher level of abstraction.

Conceptual Model

The result of our analysis is a process model of handling friendship requests depicted in Figure 16. The figure illustrates the process by which network construction occurs on an example of handling one friendship request and tries to encompass the context in which this process takes place. In this process we can recognize the elements of the coding paradigm (Strauss and Corbin 1998), including *causal conditions* that influence the user's attitudes and intentions towards a FR, possible *actions* at user's disposal when it comes to dealing with a request, and an array of *consequences* which follow as a result of a chosen strategy. Whenever an 'encounter' with a potential 'friend' takes place (FR is received or a potential FR is being considered), users initially question the *degree of familiarity* with the person in question. Outcomes of this evaluation either directly lead to an *attitude* or are further complemented by the cost-benefit assessment of *secondary benefits vs. costs*. This process might be influenced by the social environment – other users of SNS. Once the attitude towards a certain FR is formed, it is translated into *behavioral intention*, which, if the broader context (*intervening conditions*) is favorable, leads to its realization (actions). The result is a set of *consequences*, can be related to the *network* itself, the possibility to obtain *social capital*, *cognitive benefits of enjoyment* or *sense of self* as well as such negative aspects as *privacy concerns* or *information overload*. The model is circular, so that the consequences that are achieved can be used to update the strategy for the assessment of the following friendship requests. Thus, if the user had a good experience of adding someone he did not know so well, but obtained some unexpected benefits from that person, he might be more favorable when assessing a friendship request from a person of similar tie strength in the future. Thus, a person's *heuristics* used for assessing a FR are updated as a result.

Phenomenon

The phenomenon emerging in our study is the *attitude* and *intention* towards a friendship request. As revealed by our data, and confirmed by many behavioral theories, *attitude*, reflecting an evaluative judgment (e.g. *good–bad*, *harmful–beneficial*, *desirable* - *undesirable*), is the most powerful predictor of *intention*, which in turn, determines behavior (Ajzen 1991; 2005; Crites et al. 1994; Fishbein and Ajzen 1975). As construction of an individual network is in most cases under one's own volitional control (Ajzen 1991), the *intention*, reflecting individual readiness to perform a certain action (Ajzen 1991), typically gets directly translated into *action*. The process is as follows: *Positive attitude* usually leads to *intention of accepting* a friendship request or initiating a *search* for the person in question. At the same time a

negative stance results in *leaving the request pending*, a decision to *collect additional information*, *ignore* the request or *avoiding sending* one. As our phenomenon is action-oriented, *attitude*, *intention* and *action* interact closely with each other, as illustrated by the following example: “If I do know them I will accept (*TIE STRENGTH: high; INTENTION: accept*). Sometimes I accept it, but on a limited profile for people that I don’t really know (*TIE STRENGTH: no familiarity; ACTION: accept*). There are people at the university who have added me that I never spoken to and I feel kind of socially obliged to add them (*ATTITUDE: negative; PEER PRESSURE: high; INTENTION: accept/send*)” (Q). The intention in these examples is revealed by the desire of certain behavior (e.g. will accept, I feel obliged to accept), whereas actual behavior has a firm connotation or is expressed in the past (I accept, I accepted).

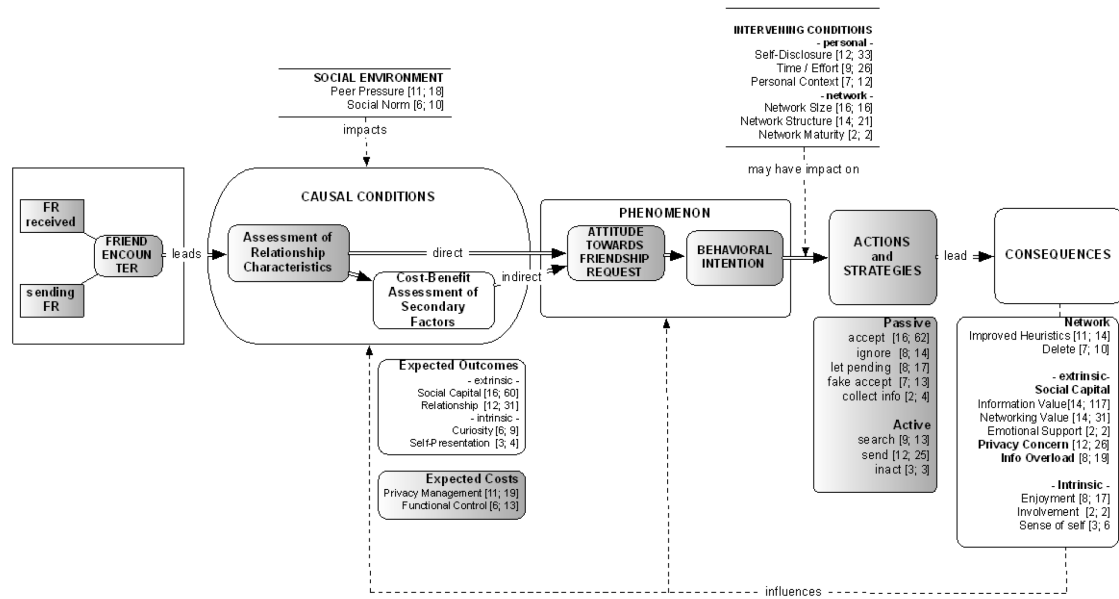


Figure 16 **Process Model of Handling Friendship Requests**¹⁴

Causal Conditions

Nature of Encounter: Send vs. Accept

Following our data, ‘nature of encounter’ with a ‘friend’ represents a significant determinant of *attitude* towards a particular friendship request (see Figure 16). SNSs typically allow users to construct their networks in two ways: (1) *passive* path – involves receiving a friendship request and requires a *response*; or (2) *active* path – typically takes place through encounter via suggestions, or by remembering someone and *sending* a friendship request. We find that sending vs. responding to a request provides a simple cue

¹⁴- The first number in square brackets next to each category reflects a number of respondents mentioning this category (max. 16). The second number reflects a number of times this category was mentioned in all transcribed interviews. Even though frequency of occurrence of a particular category maybe biased, these numbers give reader an additional insight into the relative importance of a particular category in the overall conceptual model.

underlying the very basic heuristics users adopt when forming their *attitude*. Generally, users are more prone to accept than to send friendship request, since sending requires more effort and motivation: “I *wouldn't probably make the effort of finding new people on Facebook, but if somebody finds me, I will of course accept*” (Q). Some respondents even claimed to never send friendship requests to others. People have a more strict set of motivations to send friendship request than to accept them: “I *could add him [send a FR] if he will take the same class as me...otherwise why do I need him?*” (Q).

Relationship Characteristics

As our data shows, attitudes that users develop towards a friendship request are tightly related to various *relationship characteristics* between parties involved (see Figure 16). Particularly *tie strength* appears to play a key role in the attitude formation process: it is the most frequently mentioned category in our study and all of the 16 interview respondents claimed to evaluate a friendship request on the basis of how well they knew a person. Moreover, assessment of relationship characteristics is usually the first step towards handling friendship requests. Considering the results presented in part 1 of this dissertation, this result is not surprising, as tie strength has been shown to be the main heuristic cue people employ to identify relevant information on the SNS platform. Therefore, tie strength can be one of the main drivers behind the process of network construction as well. Despite the fact that tie strength can be a highly granular characteristic and it is not embedded in the platform, our respondents consistently differentiated between strong and weak ties when they were evaluating their network construction behaviors as well as those people they did not know at all (strangers or no ties). This is also supported in the literature, as the authors have been focusing on identifying whether strong or weak ties are better positioned in the overall network structure (Granovetter 1973, Burt 1992). We explore the impact of these three different levels of tie strength on the attitudes towards friendship requests people receive and send on SNS.

Strong Ties: Requests from people users know *well* typically result in positive evaluative judgments: “I *am always happy when people from my past send me an invite*” (Q). Similarly, *sending* a FR was not viewed as a challenge whenever users encountered a good acquaintance via suggestions, common friends, or just by memory recall: “*If I see that one of my office colleagues is on Facebook, I would definitely send a request, because I have nice memories of my work*” (Q). However, our data shows that the negative valence of other factors, such as lack of personal predisposition, expectations about the need to exert higher control over one’s self-disclosure, and low probability of future face-to-face interaction may outweigh the importance of high degree of familiarity and lead to negative attitudes: “*This girl I know well, but I don't like her, so I ignore*” (Q). Therefore, although tie strength is an important, but not necessarily the only factor users consider when building their networks.

Weak Ties: A variety of motivations are at play when it comes to handling friendship requests from weak ties. Some respondents valued the opportunity to keep in touch and possibly obtain information or other benefits from the people they did not know very well: “*I went on a hiking trip this summer and he was the guide of the group and we talked and he is cool and that's why I added him to know what other expeditions or trips they have in the mountains*” (Q). However, especially when exacerbated by other factors, such as expected necessity to engage in privacy management, receiving such a friendship request led to a

negative attitude: “I know their name, I know their face, but I never talk to these persons, and it is strange to show my life to someone that I don’t tell my life in real” (Q). Lack of time and unwillingness to take an effort—intervening conditions in our model - also often prevent users from sending a request to a weak tie: *“I really don’t feel I need to have her in my friends list ... I wouldn’t make the effort” (Q).* Therefore only when users are extrinsically motivated or the broader structural context is favorable, they will add someone they do not know well.

New Ties: As a rule of thumb, most respondents in our sample claimed not to add people they do not know: *“100% I wouldn’t add people that I hadn’t seen before. I would never add anybody that I don’t know” (Q).* With no existent relationship at hand, other relationship-related factors (e.g. common ground) may come into play. These, however, should be strong enough to outweigh the absence of familiarity: *“I still add some, when I see that there are really a lot of common people, and probably they come from the university where I studied before” (Q).* Thus, despite allegedly strong attitudes regarding ‘zero tolerance to strangers’, many users were willing to bend their rules when faced with a real situation providing evidence for the gap between claimed attitudes and real behavior.

Secondary Factors

The assessment of the secondary factors will be determined by weighing the benefits and the costs of adding a certain contact into the list in a process of cognitive calculus. Privacy Calculus Model postulates that users will disclose information on the Internet only when they perceive the benefits to outweigh the possible privacy risk (Dinev and Hart 2006). Applying this model to SNS, enjoyment and convenience in maintaining relationships can induce SNS users to reveal personal information (Krasnova et al. 2010a). Therefore, when dealing with friendship requests we assume that users will engage in a similar cognitive calculus process, where they will accept the request only if the benefits of adding a contact will outweigh the costs. At the same time, they will be bounded by the constraints posed by their social environment – either the specific friend in particular or all other user in general. As relationship characteristics are the primary ones to be assessed, we assume that lower the relationship with the person, the more users will engage in evaluating the secondary characteristics as depicted in the Figure 16.

Expected Outcomes as a result of interactions on SNS, often constitute an important part of the individual decision-making process to add someone to the network. Outcomes can be intrinsic – that is possessing an end in itself and existing within an individual, or extrinsic – referring to some external benefit resulting from the relationship and thus involving not only the individual in question. What concerns extrinsic outcomes, we distinguish between the ones related rather to the development of the *relationship* with the person in question per se and *social capital* benefits that may result from the maintenance and development of these relationships. On the other hand, intrinsic benefits center around presenting oneself as being connected to a large network or satisfaction of one’s curiosity. We explore these benefits in detail below.

Participants stress the low costs of maintaining relationships with a large network of weak ties: *“[Facebook] is a great catalyst for social interaction, because you can keep in contact with so many more people than you would be able to with conventional methods” (Q).* Apart from keeping up the relation-

ship, participants believed that SNSs help them bring a relationship with less or unfamiliar people to a new level: *"Without Facebook there would have been no social relationship at all"* (Q). Our findings are supported by empirical evidence which confirms the importance of social interaction and relationship maintenance that induce users to participate on SNS (e.g. Ellison et al. 2007; Krasnova et al. 2010a).

A more tangible benefit resulting from maintaining the relationships is the access to the resources of others and the ability to obtain them when needed, such as getting advice, help, information, and often accommodation commonly known as social capital (Bourdieu 1985). These anticipated benefits especially induce users to add less familiar, but presumably 'useful' contacts to their lists: *"[I would add]...if the person is male, because I am single ...or someone working in the World Bank or such..."* (Q). Having a larger and diversified network is viewed as beneficial for the future: *"He is the first entrepreneur friend I know and he sent an invite, so maybe this will be helpful sometime later"* (Q), thus corroborating the strength of weak ties argument proposed by Granovetter (1973).

Self-Presentation is the ability to present the desired image of oneself, which is one of the main functions supported by SNS (Donath and boyd 2004). Users seemed to place certain value on their contact list when presenting themselves to others on SNS: *"I always think that it's better to have more friends, because it's not obliging to anything, and why not"* (Q). Following our respondents, profiles with higher number of friends were perceived as more trustworthy and added more credibility to its owner in the eyes of others – a finding confirmed by previous work (e.g. Boyd and Heer 2006). However, participants also mentioned that having too many friends in their network might put a negative connotation on their online persona: *"All those people who have 500+ friends are just kind of ... collecting them"* (Q), hinting that there is an "optimal" number of friends on SNS. Studies also find that there is a cap in the number of friends one can maintain on SNS (Tom Tong et al. 2008): the benefits seem to diminish when networks go over 500 friends (Ellison et al. 2011).

Curiosity is defined as an intrinsically motivated desire for information, which is a critical motive that influences human behavior (Loewenstein 1994). SNS help to satisfy the curiosity of users by providing them with a myriad of information about their friends: *"Formy elementary school friends I was curious how they have changed... As they added me and I was confirming, I watched the pictures to find out what kind of people they had become..."* (Q). Thus, this confirms the desire of people to demand more information as an end in itself and not just to achieve extrinsic outcomes. In fact, we find that curiosity often leads users to accept a friendship request when no other reason seems convincing enough: *"I suppose I would add somebody if I met them, just out of curiosity, especially if it was a good looking girl"* (Q).

Expected Costs. One of the major concerns about adding people to one's contact list is the anticipated necessity of controlling one's self-presentation and posting behavior on the network which we unite under the term 'privacy management'. Our respondents were worried about the expected social discomfort posed, for example, by the presence of immediate family members or colleagues in their friends' lists: *"So if I think that the person should not know what I generally post on Facebook, I would not add the person. For example, I did not add my 18 year old cousin"* (Q). However, SNSs offer users refined means to manage accessibility of their information via functional controls. Our findings show that presence of

privacy settings gives users psychological reassurance that despite adding, for example, a less familiar contact to their friends' list, they could always limit access to their information via available functionality on the network: *"I can imagine adding someone because of some self-interest ...I can add this person and then restrict their access to my profile, let them see only one or two pictures"* (Q). However, users need to invest their time and effort into learning how to utilize these functional controls. Therefore, the intervening conditions such as *lack of time* or *unwillingness to take an effort* often lead to underutilization of these functional controls and thus increase in adding people to their contact list.

The opinions of others in the **social environment** are often considered when making decisions about adding people to the contact list. Respondents often felt obliged to accept a friendship request as a form of social pressure – a perception rooted in the unwillingness to offend others or appear rude to them. The stronger is the tie, the more is the social pressure from that person to accept the request: *"The person that irritates me here most, is my cousin's boyfriend. And I accepted him because I know him pretty well and he is my cousin's boyfriend"* (Q). In the case of distant acquaintances this factor was particularly noticeable when common ground was present or future interaction was expected: *"I rejected someone and then they bumped into me and it was horrible. Now I tend to just accept people"*. Interestingly, this pressure was also sometimes perceived even with respect to unfamiliar users: *"I heard about him from a friend but I never saw him. But still I feel guilty to reject"* (Q). This may result from the **social norms** on the platform that promote that adding someone is simply "a common practice": *"Usually this is how it works, because whenever I meet people it's already a tradition to log in and wanting to add this person"* (Q). Indeed, adding someone as a friend on SNS is considered less binding than, for example, asking someone for a telephone number.

Strategies and Actions

Nature of encounter – friendship request received vs. considered - is a primary determinant of actions at a user's disposal. That is, if users receive a friendship request, they rather take a passive position in constructing their network, whereas when they want to actively construct their network they have to search for people and send friendship requests themselves.

Once a friendship request is received, two basic options are available: *accept* or *ignore*. Another common alternative is to *leave the request pending* in order to delay making the final decision: *"I couldn't decide right now, but I think I will let her stay in the list before confirming or before ignoring...it's like giving myself time to think or to remember"* (Q). In addition respondents can try to *find some information* about the sender: *"If I see the picture on Facebook, then I pay more attention at school and then if I see her, I remember that I had a conversation with her"* (Q). Another intricate strategy – *false accept* – can be adopted when a user is unwilling to accept a request but at the same time cannot immediately ignore it: *"When family members send me a friend request, I first say confirm, because otherwise they would be mad, but then delete them the next day"* (Q).

On the other hand, users can either take an active position and *search* for people themselves or simply do nothing (inaction). Overall, proactive network construction is well supported by the functionality of the

site: “Facebook gives you suggestions... People that you might know, so I add them then” (Q). Searching for someone and sending a FR typically requires stronger reasons than would be necessary if the user had to make a decision about a received request. For example, expectation of possible benefits may motivate users to make an effort of sending a friendship request.

Intervening Conditions

Intervening conditions, related to personal characteristics or particularities of existing networks, can have an effect on actions users undertake. For example, favorable personal context in the moment of taking a decision about a friendship request can impact behavior considerably: “I’m just new in the city and I’m just getting to know people. ... so I add everyone” (Q). Especially the size and structure of the network of friends play an important role in dealing with friendship requests. Logically, if the network is already large, people are more reluctant to add others than if they just have a few friends: “I think 450 friends is too many, there are useless people that I wouldn’t have a conversation... and I would like to clean... Facebook suggests me to get in touch... but I don’t add her because there is no use” (Q).

Consequences

As a result of their network construction behavior, certain consequences may be achieved. We distinguish between direct or network-related outcomes as well as indirect ones, which can, as similar to the secondary causal conditions, be subdivided into extrinsic and intrinsic ones.

Referring to direct outcomes, first and foremost as a result of adding friends users update their decision process – or heuristics – for dealing with friendship requests: “There are a few people I got an invite from and I accepted it, but I barely know them... So I wouldn’t want my homepage filled with updates about people I really don’t want to know about so much” (Q). Indeed, negative experience with *information overload* – a possible and likely consequence of the inadequate network construction behavior (Koroleva et al. 2010) – may lead a user to be more considerate in accepting friendship requests in the future and even delete main “spammers” from the network.

A myriad of extrinsic outcomes can result from adding people to the network, the most valuable of which are the gains in social capital. They encompass (1) various *informational benefits* including finding out useful information, broadening the horizon or being socially updated; (2) *networking value*, such as, getting help in matters where one’s own expertise is not enough: “If you’ve got a professional problem with studies and someone of your friends are good at that, you would ask them for help?” (Q); (3) or even *emotional support*: “I know my friends are always there for me” (Q). On the negative side, users may suffer from elevated *privacy concerns* as a consequence of uncontrolled network expansion. Moreover, expanding the network may result in several intrinsic benefits, most commonly mentioned of which were: (1) *enjoyment*, (2) *increased sense of self*, and (3) *user involvement* on the platform.

2.3 Empirical Study

Research Model and Hypotheses (C1)

Sending and *accepting* a friendship request are two ways of constructing a network. As the process model depicted in Figure 16 shows, tie strength represents the most crucial heuristic when it comes to handling friendship requests. Generally, it holds that the more people know each other the more likely they are to accept or send a friendship request to one another. Additionally, users assess *secondary factors* – in a process of cognitive calculus when determining the final outcome. However, our interviews show, that these factors play a more important role, the weaker is the relationship with the person in question. However, in the next step we would like to test this proposition empirically, and therefore explore if and how strongly the secondary factors are likely to influence the decision to accept/send a friendship request from/to people of various degrees of familiarity.

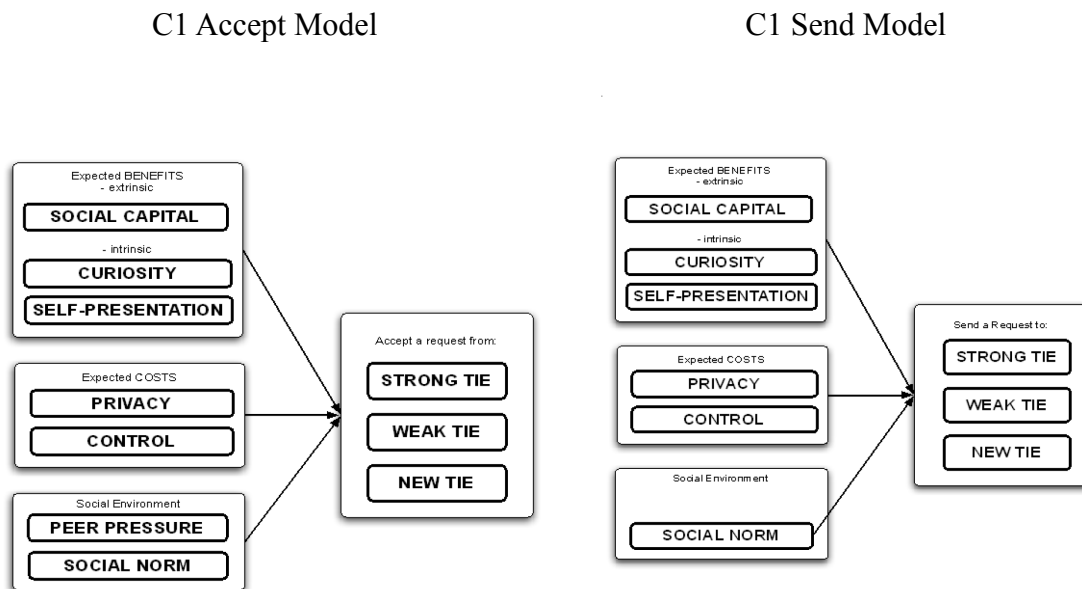


Figure 17 **Research Model C1**

We test two empirical models, – one for send and another for the accept scenario, which are depicted in Figure 17. The independent variables in these models are mainly the secondary factors introduced in Figure 16 – social capital, self-presentation and curiosity on the benefit, and privacy management and control on the cost side. Additionally, the impact of social environment operationalized as peer pressure and social norm on accepting/sending friendship requests is tested. It is important to note, however, that as operationalized in our model *peer pressure* can only be the part of the “Accept” model. *Relationship* is

the only secondary factor recognized in the qualitative study that is missing in our empirical model¹⁵. The dependent variables in each model are the likelihood to send/accept a friendship request from/to the people of three tie strengths – strong, weak and new ties. We want to explore which of the factors recognized as the benefits, the costs and the social environment have impact on the decision to accept/send a friendship request from/to people of various degrees of familiarity and therefore do not propose any specific hypotheses.

Study Design

Students at a U.S. university were offered to participate in the online survey in exchange for several points of extra credit. Taking part in the study was voluntary, with Facebook membership and the age above 18 stated as conditions for participation. Even though our choice of the target audience was partly dictated by practical reasons, behavioral research suggests that results obtained on the basis of college samples are largely generalizable to the overall population (Kruglanski 1975). Moreover, 96% of students use Facebook in a typical American university (Facebook 2011a), providing evidence for students representing an important user group. The responses were collected in Fall – Winter 2009/2010, with a final net sample consisting of 229 observations. Median age of the respondents was 22 (mean 24); 63.3% were male and 36.2% were female; 71.2% had U.S. origin. Majority of the respondents were majoring in business-related disciplines: 26.7% in Management Information Systems, 20.9% in Finance, 18.7% in Marketing, 17.1% in Management. Median number of Facebook friends for respondents was 305 (mean 357, min 3, max 1860).

To operationalize constructs in our study we relied on the existing scales wherever possible. However, in many cases scales had to be modified or developed anew to reflect the specific context of our research. The constructs and the items that were used to measure them are presented in Appendix 6. Content validity of such scales was ensured via intense discussions with SNS users: As a result a few items were either removed or improved. Unless specified otherwise, all items were anchored on a 7- point Likert scale, with all constructs modeled as reflective. Particular attention was paid to the operationalization of our dependent variables: *Likelihood of Accepting / Sending a friendship request*. A variety of situations were formulated in order to reflect *strong, weak and new ties*. Each situation was then used twice: to evaluate (a) the likelihood of accepting such friendship request and to assess (b) the likelihood of sending a friendship request to such person. Once the data was collected, hypothesized differentiation across the degrees of tie strength was verified on the basis of Exploratory Factor Analysis (EFA): As a result, one item exhibiting poor loading was removed.

¹⁵ - Even though omitting this factor definitely resulted in the loss of the explanatory power of the tested models, a significant impact of this factor on SNS participation and willingness to engage with others has received strong support in our qualitative study, as it was mentioned more frequently than any other secondary factor. Furthermore, its relevance has been validated in other quantitative and qualitative studies (e.g. Boyd 2010; Krasnova et al. 2010a; Livingstone 2008; Lewis and West 2009).

Operationalization of the *social capital* construct aimed to reflect the usage of one's contact list for personal gain, e.g. information or job search, similar to the items of the bridging social capital formulated by Williams (2006) was taken as a basis and then modified and extended. Six items from the Social Curiosity Scale by Renner (2006a) were selected as the most suitable to operationalize *curiosity* in the context of our study, as they underscore social aspects of this construct, namely "interest in how other people think, feel, and behave" (Renner, 2006b, p. 305). Items for the *functional control* construct were borrowed from Krasnova et al. (2010b) and aimed to capture user's perceptions of control over one's information and actions of others via privacy settings. Items measuring other constructs – *peer pressure*, *self-presentation*, *privacy management* and *social Norm* – were self-developed.

Estimation Results

Partial Least Squares (PLS) approach was chosen to evaluate Structural Equation Models depicted in Figure 17. The choice of this approach was dictated by several reasons. First, PLS is a preferable methodology in situations when the study has an exploratory nature with the theory behind the model still in development (Fornell and Bookstein 1982). Second, taking into account that many of the variables in our sample were not normally distributed, PLS was particularly suitable as it does not place strict restrictions on data distribution. All calculations were carried out using SmartPLS 2.0.M3 (Ringle et al. 2005). Evaluation of our models has been done in two steps: assessment of the measurement models was followed by estimation of the structural models as described below.

Table 21 Quality Criteria of Constructs for Model C1

Construct	"Accept" Model				"Send" Model			
	Mean	CA	CR	AVE	Mean	CA	CR	AVE
<i>Dependent Variable</i>								
Strong Tie	6.1	.9	.92	.71	5.4	.84	.89	.61
Weak Tie	4.5	.86	.91	.7	3.5	.84	.89	.67
New Tie	2.9	.93	.95	.74	2.16	.95	.96	.78
<i>Independent Variables</i>								
Social Capital	4.19	.78	.89	.6	4.19	.78	.86	.6
Self-Presentation	3.2	.94	.95	.8	3.2	.94	.95	.8
Curiosity	4.19	.83	.87	.53	4.19	.83	.88	.55
Privacy Management	4.59	.85	.89	.66	4.59	.85	.88	.65
Control	4.32	.86	.87	.64	4.32	.86	.9	.7
Peer Pressure	3.07	.82	.88	.65	3.07	n.a.	n.a.	n.a.
Social Norm	4.1	.79	.86	.6	4.1	.79	.85	.6
Benchmark	-	.7 ¹⁶	.6 ¹⁷	.5 ¹⁸	-	.7 ¹⁶	.6 ¹⁷	.5 ¹⁸

¹⁶ - Cronbach's alpha (CA) threshold is 0.7 (Nunnally 1978)

¹⁷ - Composite Reliability (CR) threshold is 0.6 (Ringle 2004)

¹⁸ - AVE threshold is 0.5 (Fornell and Larcker 1981)

Looking at the descriptive statistics presented in Table 21 (column “mean” for the different types of ties in the two models) we can already make some of the interesting conclusions, supporting the insights of our qualitative study. By comparing the means between the various levels of tie strength (for both send and accept models) we see that the stronger the tie, the higher the likelihood of accepting or sending a friendship request. By comparing the means between the “send” and “accept” models of each tie strength, we see that people are more likely to accept than to send friendship request, notwithstanding the level of familiarity. Please note that the differences across all items were statistically significant.

Validity of our measurement model was checked by evaluating convergent and discriminant validity of the measured constructs. Convergent validity shows that constructs are reliable and that they are measuring what they are supposed to measure. It was assessed by estimating the indicator reliability, composite reliability (CR) and average variance extracted (AVE) parameters. Indicator reliability is ensured when factor loadings exceed the level of 0.7 (Hulland 1999), whereas lower values are also possible as long as the indicators together appropriately reflect the construct, with 0.4 as the lowest threshold (Bagozzi and Baumgartner 1994). This criterion was met for all items in our models, with only four and two indicators lying between 0.55 and 0.60 in the “Accept” and “Send” models respectively and the rest exceeding the benchmark of 0.7. The composite reliability (CR), Cronbach’s Alpha (CA) and Average Variance Extracted (AVE) parameters for each of the constructs tested in the model are depicted in Table 21. The results allow us to conclude that convergent validity of our constructs is assured, as all constructs exceed the benchmark values for the required indicators. Discriminant validity provides evidence that the constructs in a model are sufficiently different from each other. It is ensured when the square root of AVE for a particular latent variable is higher than the correlation between this variable and any other latent variable included in the model (Fornell and Larcker 1981). This requirement was fulfilled for all constructs in both models.

Table 22 Estimation Results of Model C1

Variable / Model	“Accept” ¹⁹			“Send” ¹⁹		
	Strong	Weak	New	Strong	Weak	New
Social Capital	0.03	-0.05	0.00	0.26***	0.11*	0.04
Self-Presentation	-0.08	0.05	0.19***	-0.1	0.14**	0.22***
Curiosity	0.02	0.10	-0.02	0.14*	0.04	-0.09
Privacy Management	-0.12	-0.10	-0.06	-0.19***	-0.04	0.04
Control	-0.06	0.04	0.14	0.05	0.16***	0.21***
Peer Pressure	0.05	0.19***	0.23***			
Social Norm	0.07	0.25***	0.20***	0.07	0.26***	0.27***
R-squared (R²)	3.0%	16.1%	23.0%	13.6%	20.0%	21.7%

¹⁹ - ***- significance at 1%, ** -significance at 5%, * - significance at 10%

When using PLS, evaluation of the structural model encompasses estimation of the R^2 -values for dependent constructs, the path coefficients and the corresponding p-values²⁰. The results are summarized for the two tested “Accept” and “Send” models in Table 22. On the basis of these results we can conclude whether the secondary factors play a role when accepting/sending requests to people of various degrees of familiarity. For the purposes of explorative research, R^2 is considered high when it is above 0.65, R^2 of over .33 is considered sufficient, and R^2 of over .19 is also accepted (Hansman and Ringle 2005).

What concerns accepting friendship requests, we observe that for the strong ties, the secondary factors explain only 3.0% of variance. This occurs due to the fact that none of the recognized secondary factors is a significant predictor of accepting friendship requests from strong ties. For weak ties, the explanatory power is at 16.1%. Out of the recognized secondary factors, peer pressure (0.19***) and social norm (0.25***) are significant predictors of accepting requests from weak ties. For the case of new ties, the secondary factors self-presentation (0.19***), peer pressure (0.23***) and social norm (0.2***) explain 23% of the variance in the likelihood of accepting a friendship request. The explanatory power of the accept model is only sufficient in case of new ties. For the other type of ties, it is rather the tie strength itself that is a significant predictor of the likelihood to accept the friendship request, or there are other factors in play that impact the desire to accept friendship request from strong and weak ties.

The predictive power of the “send model” is considerably higher than that of the “accept” model, independent variables explain 13.6%, 20.0% and 21.7% of variance in the *likelihood of sending friendship requests* to *strong, weak and new ties*, respectively. Taking into account the explorative nature of this study, such explanatory power of the “Send” model is satisfactory. We observe that the secondary factors play a more important role when sending friendship requests. Social capital gains (0.26***) and also marginally curiosity (0.14*) positively, whereas privacy management (-0.19***) negatively impacts the likelihood of sending friendship requests to strong ties. When the friendship request concerns the weak tie, social capital gains (0.11*), the desire to self-present (0.14**), functional controls (0.16***) offered by the platform as well as social norms (0.26***) impact the likelihood of sending it. Additionally, self-presentation (0.22***), functional controls (0.21***) and social norms (0.27***) are significant predictors of sending friendship requests to new ties.

2.4 Discussion

We initially relied on the grounded theory approach to develop a comprehensive model that explains the dynamics behind a network construction behavior. A conceptual model derived through a qualitative analysis of the interview data was then tested in a quantitative study. Combining results of these two research approaches together, our study delivers an array of insights into the individual network construction behavior. Below we discuss the implications of our findings and compare them to the existing knowledge as suggested by Strauss and Corbin (1998).

²⁰ - p-values were derived on the basis of bootstrapping results with 200 samples.

Based on our qualitative data, whether a friendship request is *received* or *considered* to be sent has important consequences for the network construction process. Many respondents in our sample claimed to “generally just accept people who add [them] but not [to] actively seek them” (Q). The quantitative results in Table 21 show that respondents were always more likely to accept a friendship request than to send one regardless of the degree of familiarity and other contextual factors. This may be explained by the fact that there is “more *status involved in being added*” as opposed to “*doing the adding*” (Lewis and West 2009). Alternatively, as most user networks are quite mature, users may not be willing to extend major efforts to deliberately expand them even further. Also this can be explained by the fact that there is not much thought involved when accepting friendship requests, whereas sending requires much more processing effort and motivation. As people are cognitive misers who are not willing to spend extra effort on the network, they might be less prone to send friendship requests themselves.

Interestingly, empirical test of the “accept” model reveals that no factor is critical for accepting a friendship request from a strong tie. This is in line with our qualitative findings which show that, with rare exceptions, knowing a person well is generally enough to accept a friendship request. At the same time, there can be immense variation in attitudes when it comes to accepting friends who are less familiar. These findings are in line with previous studies. For example, Boyd (2010) shows that while accepting close friends is a usual practice, teens have higher reservations when it comes to classmates they barely know. Integration of ‘strangers’ into one’s contact list causes even more resistance (Livingstone 2008). We find that only the social environment in form of the peer pressure and social norm can induce users to accept those less known. When receiving a request, people feel obliged to accept it, as they do not want to appear rude to others (Boyd 2006, p.8). Interestingly, we find that peer pressure is also an important predictor when accepting requests from new ties, contradicting a popular opinion that users see “*littlesocial cost to rejecting Friend requests from strangers*” (Boyd 2010, p. 97). This is well supported by the social norms present on the platform that encourage users to connect with many others – thus supporting the networking function many SNS are trying to offer.

What concerns the “send” model, we observe a certain cognitive calculus process when users make decisions about adding others to their contact list. The secondary factors we explore are more important predictors of the sending behavior than accepting. Moreover, different factors are at play when sending friendship request to strong as opposed to weak or new ties. For example, when considering to send a friendship request to a strong tie, people weigh the benefits of social capital and curiosity about that person against the necessity to engage in privacy management of their disclosures. On the other hand, it is rather the desire to present themselves as being connected to a large number of others that motivates people to add weak and new ties. Some users may feel embarrassed by the small size of their network, and thus deliberately expand it - behavior known as ‘*collecting*’ (Donath and Boyd 2004). At the same time, the possibility of social capital gains do not seem to motivate friendships with weak ties or ‘strangers’: as they do not know these people (well), they can not objectively assess which information they possess – underscoring the importance of transactive memory for gaining benefits recognized in previous studies (Borgatti et al. 2009). Although SNS offer some contextual information about these ties, the li-

mitted information on the profile it may be either difficult for users to assess what value they can extract from others.

Interestingly, people are more worried about people they know well having access to their information rather than those they do not know (well). This is counterintuitive, but highlights the fact that people can more easily assess the risks of accessibility of their information to those they know. Well familiar people often belong to such sensitive categories as family members or work colleagues and users might prefer to avoid proactively initiating such ‘friendships’. What concerns other people, it is hard to assess how the information may be used and therefore may not cause people to deter from sending a request. Moreover, people tend to rely on functional controls through privacy settings to mitigate privacy threats coming from those they do not know (well) and thus motivate the users to send a friendship request to such people. Possibly, users find comfort in the fact that if something goes wrong they can still unilaterally limit access to their information using available functionality. Overall, importance of privacy controls for ensuring SNS participation was supported by several studies (Krasnova et al. 2009b, 2010a; Xu et al. 2008). Specifically, in her study of teens, Livingstone (2008, p. 406) notes that “the *operation of privacy settings and provision of private messaging on the sites are teenagers’ top priorities*”.

The most interesting and stable finding for most of the explored models is the positive impact of social norm on sending and accepting friendship requests from/to weak and new ties. *Social norms* represent a ‘contextual frame’ in which users interact with others, determining how requests should be handled within the context of their social network (Lewis and West 2009). Our qualitative analysis shows that users perceive Facebook as a place where it is common to make contacts beyond a close circle of friends. Indeed, it is much easier and less binding to make friends on Facebook than to exchange telephone numbers. Just by clicking the “add friend” button does not place any requirements on communication or reciprocity on the parties involved. This result may be explained by the individuals’ propensity towards ‘herding’ behavior: if everyone is accepting, I accept too. Alternatively, it can be explained by the intended nature of the platform itself – that promotes connections between less known people and even strangers thus supporting the networking function recognized already in the definition of SNS (boyd and Ellison 2008).

3 Network Structure and Information Value

In this part of the dissertation we are concerned with the outcomes of the network construction behavior and explore which structure of the network results in which informational benefits for the individual. In the section B3.4 of the dissertation we have already shown that people are more interested in the information coming from their strong rather than weak ties and process information from these two types of ties very differently. In this part we take a more nuanced view of the network structure, and explore the impact of several measures of tie strength and a measure of network overlap on information value.

3.1 Theoretical Background

Network Structure

Networks can enhance individual performance in two ways: by facilitating access to information and resources possessed by others (Granovetter 1973, Burt 1992) and by ensuring cooperative behavior (Coleman 1988). When estimating the benefits that accrue to users due to the maintenance of relationships with others, one might consider their relative network size: the bigger the network, the higher is the probability that one person in the network possesses the desired resources. More important than the size, however, is the structure of the individual social network, that determines the benefits that can be gained. Researchers study the configurations of individuals' networks on three different levels: (i) at the network level by analyzing the structure, measured by e.g. network density; (ii) at the node level of analysis by estimating the structural position of a person, with the help of e.g. a centrality measure; and (iii) at the dyad level the relationship between two people, where tie strength determines their relationship (Borgatti et al. 2009). In this paper we explore the networks of users on two levels: dyadic level by assessing the tie strength, and network level – by assessing the relative network overlap.

On the *network level* of analysis, network structure is related to the benefits users obtain from their network. A debate persists whether cohesive networks or those rich in structural holes provide more social capital benefits to their participants. On the one hand, *cohesive networks* – where most or all of the contacts are strongly tied with one another (Burt 1992, Gargoglio and Benassi 2000) - provide easy access to each other's information as well as facilitate trust, norms and sanctions. Such networks are known to be more reliable communication channels, that can verify the information that is exchanged and thus facilitate trust between the members (Granovetter 1985, Coleman 1988). Most benefits of the cohesive networks come from network closure – a property when everyone is connected to everyone. By facilitating social norms and effective sanctions, such network enables cooperation between participants and diminishes the risk of opportunistic behavior (Coleman 1988). As users receive social reinforcement from multiple users in their network, behavior spreads farther and faster in such networks (Centola 2010). The disadvantage of a such a cohesive network is that everyone possesses similar or even redundant information and therefore the benefits they provide to each other are overlapping (Burt 1992).

On the other hand, a network rich in *structural holes* – bridges between otherwise disconnected groups of people – is more beneficial because the people on either side of a structural hole circulate in different flows of information and therefore the benefits they provide to each other are rather additive (Burt 1992, 2001). The benefits of such a network mainly result from the diversity of information contained in these separate clusters as well as the ability to broker the opportunities in connecting the separate clusters of a network (Burt 1992). Thus, such networks are more advantageous contacts to others that can provide access to sparse resources (Granovetter 1973), offer comparative advantages in negotiating relationships (Gargiulo and Benassi 2000), exercise control over more rewarding opportunities (Burt 1992), and be responsible for the spread of the new ideas and behaviors (Burt 1999). A network rich in structural holes

has been found to be positively associated with better job placement, promotion, creativity, innovation, productivity and performance (e.g. Uzzi 1997; Hansen 1999, 2002).

On the *dyad level* of analysis, the discussion about the value of rather strong or weak ties in creating social capital persists. Some researchers propagate the value of strong ties, as these ties can transfer any kind of information and possess knowledge about who knows what and requires which information (Uzzi 1997, Hansen 1999). However, as strong relations tend to develop between people with similar social attributes (Fischer 1982), they are likely to possess the same information and provide redundant benefits (Burt, 2001). Other researchers, guided by the fact that weak ties are less likely to provide redundant information and more likely to connect people from otherwise diverse groups, are more beneficial for information exchange (Granovetter 1973). At the same time, weak ties are known to be opportunistic, functional and only selfishly cooperative (Granovetter 1973, Uzzi 1997). Therefore, whether weak or strong ties are more beneficial for information exchange still remains ambiguous.

Finally, it seems that many researchers do not distinguish between these two levels of network analysis and equate strong ties with network cohesion, whereas weak ties with the availability of structural holes. This is evidenced by the definition of cohesion as „*strongly interconnected ties with each other*“ (Burt 1992) and by the similarity of arguments in the discussions above. Although tie strength and network cohesion are correlated, not distinguishing between them might lead the researchers to make inappropriate conclusions about the impact of network structure on social capital. Although strong ties are more likely to occur in cohesive networks, not all of the ties are strong in such networks. For example, neighbors exhibit cohesive networks, but their connections usually lack sufficient depth to be referred to as strong ties. At the same time, ties acting as a bridges between otherwise unconnected groups can also be characterized by a strong, and not always by a weak relationship. In fact, strong ties might be necessary to realize the value contained in structural holes, as they provide motivation to exchange the information between two otherwise distinct groups (Burt 2002). Overall, both types of ties can be beneficial for information value as the frequency of interaction between strong ties can compensate for the diversity contained in the weak relationships (Granovetter 1973). The later empirical evidence finds that both the diverse network of weak ties and a high bandwidth of communication with strong ties can provide novel information, depending on the information environment surrounding these ties (Aral and Van Alstyne 2012).

Network Structure and Information Value on SNS

Findings on the value of SNS for information exchange are quite scarce, but the insights point that a broad and diversified network structure usually leads to the benefits of social capital (Koroleva et al. 2011c). Most researchers equate the weak ties with the bridging, whereas strong ties with bonding social capital benefits (Ellison et al. 2007) – a more extensive discussion of these concepts is proposed in section D2. Overall, rather a ‘bridging role’ has been attributed to SNS, as the costs of maintaining relationships with a diverse network of others are quite low (Ellison et al. 2007). One of the dimensions of the bridging social capital scale recognized by Williams (2006) is horizon broadening – which capitalizes on

the new and unexpected information that people can obtain from their network. Although bonding social capital has been initially found to result from SNS usage, the later findings disproved its potential (Vitak et al. 2011). At the same time, the increasing amount of information exchanged on SNS, induces users to prefer information coming from their strong rather than weak ties on SNS (Koroleva et al. 2011b). Recent eempirical evidence sheds some light on these conflicting findings: strong ties are better for the transfer of information on SNS, whereas weak ties transmit information that one is unlikely to be exposed to otherwise (Bakshy et al. 2012). We set out to explore the impact of network structure on the informational benefits users derive from their network.

A unique feature of SNS is easy visualization and therefore measurement of the networks of users with a better precision. Previously researchers used surveys to elicit the subjective impressions of users about their network in general or tie strength with specific people in particular. SNS allow to measure the network as a whole, as well as to assess the underlying relationships between specific people. We assume that the relationship between network structure and information value will not only be determined by the tie strength between users, but also by the relative overlap between the users’ networks. We propose to exploit the unique possibilities of SNS and to measure the networks on the dyad level of analysis, that is for each pair of users, by the strength of their underlying relationship and tapping into the network level of analysis, by their relative network overlap. Although previous studies have explored the impact of tie strength on information value (Koroleva et al. 2011b), no study so far has studied the impact of network overlap on informational benefits users derive. Moreover, we operationalize tie strength not only as the people with whom users already maintain an existing relationship, but also those weak ties that the users want to get to know better and that have a latent possibility to develop in the future. They might be even more important, as SNS effectively provide ground for the development of exactly this type of ties.

Table 23 **Categorization of Ties on SNS**

Network overlap	high	E.g. classmates	E.g. good friends
	low	E.g. recent acquaintances	E.g. lovers
		weak	strong
Tie strength			

We can therefore categorize the ties on SNS along the two dimensions - tie strength and network overlap – which although correlated, do not necessarily coincide with each other (cf. Table 23). We need not provide examples of people who have high (low) network overlap and are characterized by a strong (weak) relationship. The interesting cases are located in the lower right and upper left corners of the Table 23, that illustrate that high network overlap does not necessarily occur between individuals connected by a strong tie. On the one hand, it is possible to imagine highly overlapping networks of two users, who are connected by a weak relationship, such as for example, school classmates. On the other hand, one can be

quite close with someone, but the networks may not necessarily overlap, for example two people who live in different cities or belong to different social circles, but had a period of intensive communication at one stage of their lives, such as lovers. In our study, we aim to explore the impact of each of these two dimensions of network structure on the value of information users obtain on SNS.

We propose that tie strength and network overlap can have different impact on the value of information on SNS. On the one hand, if the tie is weak, there is low interest in information coming from that person and therefore no motivation to process such information. On the other hand, a high network overlap might result in redundant information and the ability to obtain the same information also from someone else in the network. Therefore, a combination of high tie strength and low network overlap might promise the highest benefits to the users: the diversity of the network allows to get access to the resources that one does not possess oneself, whereas the strong relationship allow to easily obtain those resources if needed.

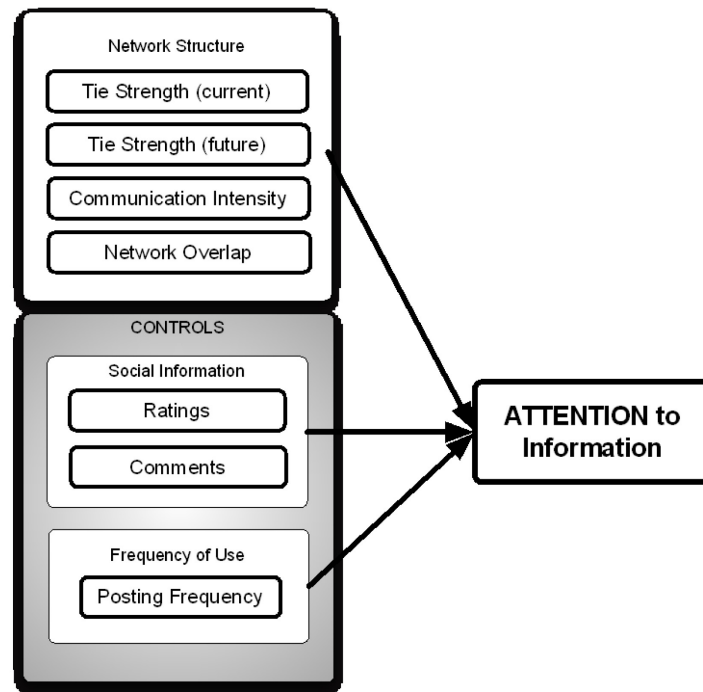


Figure 18 **Research Model C2**

3.2 Research Model and Hypotheses (C2)

Our hypothesized model is presented in the Figure 18. In line with the generic model depicted in Figure 4, we want to explore the impact of network structure on the attention users towards the information shared on SNS, as well as control for the social information and experience of using the medium. As opposed to the models tested in section B3 our main focus is the impact of network structure on the attention of users towards the information on their Newsfeed, which we measure in several different ways on two levels of analysis according to Figure 3. On the dyad level of analysis, we elicit the subjective evaluations of users about the existing tie strength as well as the desire to develop a relationship with the person whose infor-

mation is presented. On the network level, we objectively measure the network overlap of two users which will allow us to estimate their relative network density. As previous studies show (Burt 2002, Ellison et al. 2007, etc.) network structure has a significant impact on the attention users pay to the information that is shared on SNS. Let us explore each of the variables in detail and derive the hypotheses about the relationships between them.

Dependent Variable

The dependent variable of our study is the attention of users towards the information that is shared by their friends on SNS. That is, only the information that attracts user's attention in the overall information flow is the only valuable information that the user can effectively use. Attention has several meanings, the most common of which is selective processing, defined as differential processing of sources of information (Johnston and Dark 1986). In section B3.1 we introduce two modes of processing information - bottom-up and top-down approach. The bottom-up approach, also known as systematic processing, involves extensive evaluation of information and requires a significant amount of motivation, ability and cognitive resources. In contrast, the top-down approach, referred to as heuristic processing, involves reliance on cognitive heuristics – mental shortcuts that allow people to form opinions without extensively analysing the contents, internally based on certain stimuli (Ajzen and Sexton 1999, Johnston and Dark, 1986). As we have already argued in section B3.1, on SNS users will process information heuristically and increasingly react to certain stimuli – for example, the relationship with the person who posted or the rating the information has received. Some stimuli can be explicit, such as the number of ratings or comments the information has received, whereas others can be more implicit, for example the underlying relationship or the interconnectedness of the users' networks. We explore these stimuli and their impact on the attention of users in the next sections.

Independent Variables

Measures of Tie Strength

Tie strength is defined as a combination of the amount of time, the emotional intensity, the intimacy and the reciprocal services which characterize the tie (Granovetter 1973; Madsen and Campbell 1984). In the absence of a unified measure of tie strength, authors have been approximating it by the frequency and duration of contact (Granovetter 1973), social homogeneity and level of attraction (Reagans, 2005), as well as overlap in organizational memberships and social circles (Alba and Kadushin 1976). Tie strength has been found to possess two main dimensions: time spent in a relationship proxied by duration and frequency of interaction and depth of the relationship indicated by, for example, intimacy of communication and emotional support (Madsen and Campbell 1984). On Social Network Sites tie strength is especially hard to measure, as this characteristic is not reported by the platform and all connections that users maintain are referred to as “friends” (Boyd and Ellison 2008). However, Gilbert and Karahalios (2009) show how to approximate tie strength with the accuracy of 80% by assessing the available network data related to the frequency and depth of communication as well as similarity characteristics between users. In our study we measure tie strength with several dimensions: i) closeness approximated by level of ac-

quaintance; ii) affection approximated by the desire to develop a relationship; and iii) communication intensity on SNS. We want to explore how these measures of tie strength are related to the value of information users obtain from their networks.

Closeness

Distinguishing between indicators (actual components) and predictors (influencing factors) of tie strength, Mardsen and Campbell (1984) find that the best and not confounded by predictors indicator of tie strength is closeness between the users. Closeness is the measure of the intensity of a relationship (Mardsen and Campbell 1984) or level of acquaintance with the person (Petroczi et al. 2007). That is, weak ties are the ones which reflect lower levels of acquaintance, whereas strong ties – are those closer people in one's network. Mardsen and Campbell (1984) measure closeness on a three-point scale: acquaintance, a good friend, a very close friend. Gilbert and Karahalios (2009) measure tie strength subjectively by asking the respondents to indicate how strong is their relationship with the person on a continuous scale from barely know – very close. In line with these studies, we operationalize strong ties as those people users know well, and weak ties as all other people in the network.

Whether strong or weak ties are more advantageous contacts in a network has been a long running debate among the researchers. While at first it was established that strong ties are associated with information value (Coleman 1988), Granovetter (1972) advocated the strength of weak ties argument, which has been applied to multiple contexts. The functionality offered by the earlier generations of CMC, such as e-mail or discussion boards, lead the researchers to argue rather for the value of the weaker ties, as they were only possible to transmit very lean information (Daft et al. 1987) and were characterized by the lack of contextual cues (Miranda and Saunders 2003). Although the first empirical attempts supported the value of weak ties in CMC (Constant et al. 1996), the tests of the theory on new media have shown that given the time and increased frequency of interaction, they could be also used to support much richer communication than was originally assumed (Carlson and Zmud 1999).

Although weak ties provide people with access to information and resources beyond those available in their own network (Burt 1992), strong ties are more motivated to transfer all kinds and types of information (Reagans and McEvily 2003), resulting in a more efficient information exchange (Ghoshal et al. 1994, Hansen 1999). Strong ties might provide users with more valuable information due to: i) the increased frequency of interaction, and ii) the established shared meaning with these ties (Miranda and Saunders 2003). Increased frequency of communication might result in greater diversity and volume of novel information that flows between strong ties overtime compared to weak tie-relationships (Aral and Van Alstyne 2012). The shared meaning established in the long process of communication may help to transfer tacit and context-dependent information (Hansen 2002) as well as easily process information in the conditions of information overload (Carpenter 2003). In fact, on SNS users prefer information from their stronger ties, where tie strength overrides the impact of any other heuristic cues (Koroleva et al. 2011). We therefore hypothesize:

C2.1: *if users know the source of information well, they are more likely to pay attention to the information from this person on SNS.*

Affection

However, closeness is not the only dimension of tie strength. In fact, the three necessary and sufficient conditions of a relationship between two people are: i) somewhat frequent interaction; ii) usually a mutual affection; iii) a history of interaction that has lasted over an extended period of time (Krackhardt 1992). Strong relationships are the ones that are characterized by a high degree of mutual affection and a certain history of frequent interactions. Ties are considered weak, if they lack either the history of interaction and/or the mutual affection. Interestingly, tie strength is usually rather measured by the recency of contact or frequency of communication, but rarely by its affective dimension (Krackhardt 1992). However, affection usually determines the relationship: if there was no mutual affection, there would be no need to interact and, therefore develop a relationship. As relationships are not formed instantly, affection for the large part is a catalysator of interaction and relationship development. It determines those weak ties that can become strong in the future, given the sufficient number of exchanges, from those weak ties that will most probably remain weak forever. The peculiar task of the new media is not only to provide ground for the already established relationships, but also to develop newly formed ones (Haythornthwaite 2002). The relaxed norms of communication and instant information updates on SNS are especially valuable as they provide ground for increased interaction especially for this type of ties. Therefore, users might also be interested in information on SNS coming from those with whom they are not yet close, but would like to develop a relationship. We hypothesize:

C2.2: *if users are interested in getting to know the source of information better, they are more likely to pay attention to the information from this source on SNS.*

Intensity of communication

Measuring tie strength by the frequency of communication has been proposed by Granovetter (1973) and used quite often by researchers ever since (Gilbert and Karahalios 2009, Mardsen and Campbell 1984, Krackhardt 1992). Intensity of communication represents the time dimension of tie strength (Mardsen and Campbell 1984). However, frequency of contact as a determinant of tie strength can be contaminated by the type of tie and thus might overestimate the strength of ties between co-workers and neighbors (Mardsen and Campbell 1984). The physical proximity of these types of people leads to frequent, however usually superficial interactions not characteristic of strong ties. Moreover, as SNS are rather known to possess value for the weak ties due to the low cost of maintenance of such contacts (Elisson et al. 2007), and users might prefer other means to communicate with their strong ties (Vitak et al. 2011), intensity of communication on SNS might not be a good indicator of tie strength. Comparing intensity of communication and similarity of interests as predictors of tie strength, Koroleva and Bolufe-Röhler (2012) find that the latter performs better. However, intensity of communication on SNS can be used as a predictor of tie strength as well (Koroleva and Bolufe-Röhler 2012). In fact, trying to estimate tie strength with the available network data, Gilbert and Karahalios (2009) achieve 80% accuracy in differentiating between strong

and weak ties based on the myriad of factors largely related to the intensity and depth of communication on SNS. Therefore, users are also interested in information from those with whom they communicate frequently on SNS. We hypothesize:

C2.3: *if users communicate with a person on Facebook frequently, users are more likely to pay attention to the information from that person on SNS.*

Network Overlap

When we explore the impact of network structure on the value of information users derive from their network, we focus not only on tie strength, but also aim to assess the impact of the degree of relative overlap in user's networks. Several researchers were equating tie strength and network overlap, for example by using network overlap as indicator of tie strength (Mardsen and Campbell, 1984). In their attempt to approximate tie strength using available network data, Gilbert and Karahalios (2009) use structural variables, such as the number of mutual friends and groups in common as indicators of tie strength. We, however, recognize that tie strength and network overlap are two different dimensions that are merely correlated and can have very distinct impact on the value users derive from their network.

Network overlap is defined as the number of mutual contacts that the users have on the network relative to the absolute number of their connections. By depicting how interconnected the ties are between each other, network overlap can be used as a measure of network density and directly reflects the cohesion of the network. High network cohesion, as discussed in section "network structure", can be both beneficial and detrimental to social capital. On the one hand, the verifiability of information by others and the threat of sanctions makes trust more likely between people who have many mutual friends (Granovetter 1985) and thus may promote the interest in information coming from such people. On the other hand, high network density directly indicates the redundancy of user's networks, which may have detrimental impact on information value (Aral and Van Alstyne 2012) as this information can also be obtained from someone else in the network. As tie strength is a direct measure of the trustworthiness of a relationship whereas the cohesiveness of a network – an indirect one, we assume that on top of tie strength, network overlap might rather have a negative impact on information value on SNS. We hypothesize:

C2.4: *the more overlapping the networks of two users are, the less they are likely to pay attention to information from each other on SNS.*

Controls

User's attention towards information shared on SNS might be driven by other post-specific, or respondent-specific factors. Post-specific controls include the feedback that the information receives on SNS in form of comments and ratings. We have already explored the impact of comments and likes extensively in the section B3.4 of this dissertation, but in this study we limit the analysis to the presence of likes and comments as opposed to the impact of the actual amount of feedback. On the participant-specific side, we operationalize experience of using the medium (cf. Table 1) along the direction and type of use and study the participant's active posting behavior on the platform.

Feedback

SNS provide certain social contextual cues for users to process information on SNS that were not present in earlier forms of electronic communications. As we have discussed in section A2.2, users not only have the opportunity to rate the information they interact with on the platform, but can also register their opinions on the digital content they encounter. Although previously we found that the number of ratings has a positive, whereas comments – negative impact on information value (see section B3.4), in this study we do not focus on the number of comments and ratings, but on their sheer presence under the information that is shared. This is partially determined by the design of our study – as opposed to the study presented in section B3.2 where users were presented with information one at a time, in this study participants are presented with the 25 posts at the same time. The comments and ratings are shown merely as a number, but their sheer presence can be recognized while scrolling down the Newsfeed. Therefore in this condition of information overload created by the posts in this study, we hypothesize will not dwell into determining the specific impact of ratings and comments, but be simply attracted by the information that has received some feedback as opposed to the one that has none. We explain our reasons below.

Reflecting the opinions of others in the social environment (Salancik and Pfeffer 1978), the presence of social information in a post might attract user's attention to certain information that is shared. First, considering the increasing amount and varied quality of information on SNS (Koroleva et al. 2010), social context cues can make certain information more salient to the user in the general information flow (Salancik and Pfeffer 1978). As users will be attracted to certain stimuli to determine which information to focus on, social information can serve as effective heuristic cue that focuses user's attention. In fact, feedback from others has proven valuable for ranking, filtering, and retrieving content (Bian et al. 2008). Second, users might evaluate the information which has received some ratings and comments higher. Knowledge of the other's evaluations might help to evaluate complex information: the presence of other's feedback on the information that is shared may implicitly increase the credibility of information or make it more attractive. Authors emphasize the positive impact of any type of contextual cue on information value (Dennis and Kinney 1998) and confirm the linear relationship between the number of cues and the development of shared meaning (Miranda and Saunders 2003). Therefore we hypothesize:

C2.5: *the presence of feedback from others in form of ratings (4a) and comments (4b) will induce users to pay attention to this information on SNS*

Experience with the medium

The channel expansion theory postulates that the perceptions of users about the medium are impacted by the experience users have with this medium (Carlson and Zmud 2003). As argued in section A2.3 this occurs due to the fact that people gain experience with the medium itself, with other communication partners as well as with the topics of communication through the medium. Especially the active usage of the platform determines its value: that is, if users post a lot themselves, they perceive the medium as a useful means of communication and information exchange. At the same time, as more information is shared on the network, the shared meaning of that information develops (Miranda and Saunders 2003), expressed in

the context of communication, the specific language and jargon that is used, the humor that is shared, and the hidden meaning that is implied. Therefore, as they post themselves more, they can better associate themselves with the content others post and therefore pay more attention to it. Therefore, we hypothesize that:

C2.6: *the more frequently users post on SNS themselves, the more they will pay attention to the information that others post*

3.3 Application and Study Design C2

We want to explore which factors induce users to pay attention to the posts on their Newsfeed. For this, we program another Facebook application that allows to simulate the real environment of the user on Facebook by extracting posts directly from their Newsfeed. Users had to log-in to their Facebook accounts and install the application whereby give all the necessary privacy permissions for the application to access and collect their information. Participants were presented with 25 posts, which were randomly selected out of all posts on the user's Newsfeed over the last 72 hours (of all types, from both users and pages). The posts were retrieved from the Facebook database using Facebook query language (structure similar to SQL), which is an API (application programming interface) provided by Facebook (Facebook 2011b).

In the first stage, when presented with 25 posts, the users were asked to scroll down and choose the ones which they would pay attention to. In the second stage, as tie strength cannot be measured directly with the data available on the network, users were presented with pictures of the friends whose posts they saw in stage 1 and asked to select those who: i) they know well; ii) they would like to get to know better. In the background, the application collected data about the post, most importantly the number of comments and likes it has received, the number of friends the participant has, the number of mutual friends between participant and poster, as well as the posting frequency of the participant over the last 30 days.

As opposed to the application that we have designed for the first study presented in section B3.2, this one aimed at: i) better simulating the Newsfeed experience of users by providing them with 25 posts and asking them to choose which ones they would focus on (in the first study users were presented with 6 posts one by one with more detailed questions about them); ii) along with subjective evaluations, collecting more objective data: referring to the post, the number of ratings and comments; referring to the pair participant-poster, number of mutual friends, network overlap; referring to the participants, the posting frequency of users. This allows us on the one hand, to combine the subjective evaluations of users with the objective data collected from the application itself as well as induces to process information heuristically so that we are better able to recognize the heuristics they use in this process.

The dependent variable (attitude) is equal to one if the user would pay attention to the post, otherwise zero. Tie strength is also a binary variable with strong ties operationalized as those posters that the participant reports knowing well (1) and weak ties as all others (0) and those posters the participant wants to get to know better (1) or not (0). We then operationalize feedback (ratings and comments) from other

users as a dummy variable, which is equal to one if there was at least one ‘like’ and or comment on the post at the time the application accessed the information on participant’s Newsfeed. We choose this approach as opposed to registering the number of disparate feedback, due to: i) too many outliers, especially when one compares the feedback on information posted by pages and users; ii) different presentation of these types of feedback for pages and users; iii) as users were presented with the information all at once, the exact number of likes and comments might not have been as important, compared to the fact that they were solely present (as opposed to a post without any likes and comments). What concerns the measure of network overlap, we calculate the percentage of the mutual friends the participant has with each poster relative to the total number of friends of the participant. We also add a squared version of the term in order to allow for an increasing or diminishing marginal impact of network overlap. Table 24 provides the descriptive statistics of the variables.

3.4 Empirical Operationalization

In order to operationalize Hypotheses C2.1 through C2.6, we make a number of assumptions about the relationship between our observed binary dependent variable, which takes on the value 1 if the participant marked the post as one (s)he would pay attention to and 0 otherwise, and our set of independent variables of interest (see Table 24). We postulate that the information value of a post can be represented by a continuous latent variable y^* , which in its turn is a linear function of a set of post characteristics (included in matrix X) and variables depicting the relationship between the poster and participant, in particular the declared tie strength and network overlap variables (included in matrix W). To allow for deviation from our specification an idiosyncratic error term, ε , is included. Formally we then have:

$$y^* = X'\beta + W'\gamma + \varepsilon$$

When y^* passes an unobservable – participant i specific – threshold μ_i , the respondent chooses to pay attention to the post in question. In our survey setup this is the equivalent of the participant i marking post j as one that (s)he would pay attention to. In that case our observable binary dependent variable takes on the value $y_{ij}=1$. The relationship between our dependent variable and X and W can be represented as:

$$y_{ij} = \begin{cases} 0 & \text{when } y_{ij}^* < \mu_i \\ 1 & \text{when } \mu_i < y_{ij}^* \end{cases}$$

The participant specific ‘attention threshold’ μ therefore includes all personal characteristics of the participant which (i) impact this theoretical ‘attention threshold’ such as and (ii) are constant over the twenty-five evaluated posts. This set includes all participant specific variables such as educational attainment and attitude towards the SNS²¹. While μ itself is unobservable, the twenty-five evaluations collected from each participant allow us to consistently estimate it while estimating the parameters of interest β and γ .

²¹Note that μ includes such elusive unobservables such as the participant’s general mood on the day of the survey for as far this variable impacts all of the evaluations equally.

This is done by rewriting the relationship between our dependent variable indicating whether the participant i would pay attention to post j (y_{ij}) and the vector of post characteristics (x_{ij}), variables indicating the type of relationship (x_{ij}), participant specific threshold (μ_i) and the idiosyncratic error term (ε_{ij}).

$$y_{ij}^{**} = y_{ij}^* - \mu_i \Rightarrow y_{ij}^{**} = x_{ij}'\beta + w_{ij}'\gamma - \mu_i + \varepsilon_{ij}$$

with

$$y_{ij} = \begin{cases} 0 & \text{when } y_{ij}^{**} < 0 \\ 1 & \text{when } y_{ij}^{**} > 0 \end{cases}$$

If we now assume that ε_{ij} follows a logistic distribution with a (standardized) variance of 1, the above empirical specification can be estimated via a panelized version of a logistical regression, (Wooldridge 2002). The participant specific ‘attention threshold’ (μ_i) can then be estimated via *fixed effects*, which assume independence between the μ and ε , or *random effects*, which assume independence between μ and X and W .

3.5 Descriptive Statistics

The responses were collected using snowball sampling, that is virally marketed through friends of friends of the authors. In total, 152 people completed the survey. After removing respondents with unbalanced number of posts (less than 25), 3025 observations from 121 respondents were left for analysis. Our sample of 121 respondents consists of ca. 40% male and 60% female respondents, who are on average 25 years old (age range: 19-52). This can be considered quite representative of a larger part of, Facebook population (Eldon 2010, Morrison 2010).

The descriptive statistics for the model variables are presented in Table 24. Most of the variables used in the study were operationalized as dummy variables, as the study involved processing a large amount of information and we could not induce users to evaluate all of it on a more granular scale. Moreover, we aimed to make the study as similar to the real SNS experience as possible. Likes and comments were also recorded on a binary scale – a post could rather have them or not (as this is the most visible information for the user, and not the actual number of likes or comments). As such, 64% of posts had at least one like, and 50% of posts had comments. Additionally, the application collected how much participants were posting in the last 30 days²². We find that on average participants post 15 pieces of information (cf. Table 24).

What concerns tie strength, users were asked to choose those users they know well as well as those they would like to get to know better. According to the data in Table 24, we see in that most of the people who users list as ‘friends’ on Facebook are rather weak than strong ties: out of all friends whose information was collected, users identified 20% as strong ties, and 8.3% as those weak ties that they want to get to

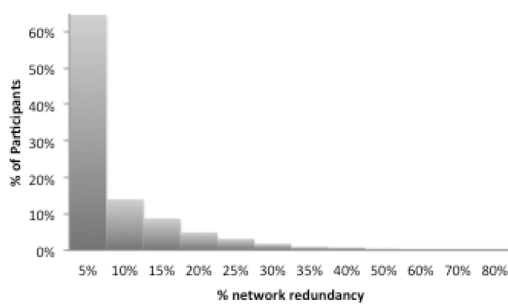
²² - we are able to collect the data from Facebook only for the period of the last 30 days.

know better This is quite realistic, considering the immense networks users maintain: on average the people in our sample reported having 298 friends on Facebook (st.dev: 215; range of 21-1390), which is much higher than the average of 130 reported by Facebook.

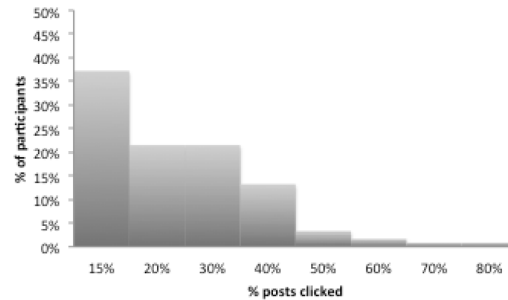
Table 24 **Descriptive Statistics of Model C2**

Variable	Mean	Std. Dev
Dependent variable - y		
Pay attention to the information? (1 / 0)	0.203	0.402
Post specific variables - X		
Are there any likes under the post? (1/0)	0.640	0.474
Are there any comments under the post? (1/0)	0.501	0.5
Participant-Poster variables - W		
Tie Strength 1 - Know poster well? (1/0)	0.191	0.401
Tie Strength 2 - Want to get to know poster better? (1/0)	0.083	0.276
Tie Strength 3 - Communicate frequently with the poster on Facebook? (1/0)	0.086	0.281
Network overlap (% pts.)	5.864	9.011

What concerns the network overlap depicted in Figure 19a, users indicated that on average they had 14 friends in common (stdev: 25, range: 0-617), which compared to their absolute size of the network is not so high. Relatively, it comprises 5% of the whole network, although network redundancy can also be as high as 73%. The distribution of network redundancy shows that for 80% of participants the average network overlap does not comprise more than 10%.



19a. Network overlap



19b. Posts that users pay attention to

Figure 19 **Frequency distributions of Model Variables in Study C2**

As each user was presented with 25 posts that were directly collected from the user's Newsfeed and asked to pick the ones (s)he would attend to, we can assess the overall usefulness of information that is provided by SNS. What we observe in Figure 19b is that out of all 25 posts, users were on average interested in

only ca. 20% of them (stdev: 0.14, range: 0-72%). If we look at the distribution of % of posts that arose attention, we see that most users are interested in not more than 40% of them.

Concerning our explored variables, Table 25 gives an overview of correlations between the measures of tie strength and network overlap. We see that the tie strength 1 is significantly related to all the other variables, which implies that any prudent operationalization of this variable ought to include both the other two tie strength measures and the network overlap variable. Specifically, we find that tie strength 1 and 2 are negatively related: users clearly distinguish between those they know well and those they want to know better. Tie strength 1 and 3 however, are strongly related, from which we infer that users communicate more frequently with those they know well than other friends. We also find that network overlap and tie strength 1 are positively related, which indicates that users tend to share more friends with those they know well. Curiously enough, users don't report communicating (significantly) more frequently (tie str. 3) with those that they want to get to know better (tie str. 2) and neither do they share significantly more or – more plausibly – less of their network with these users. Finally, we see a significant, albeit not that strong, correlation between communication intensity (tie str. 3) and network overlap, implying that communication intensity coincides with having more mutual friends.

Table 25 **Pairwise Tetrachoric Correlations**

	tie str. 1	tie str. 2	tie str. 3	network overlap
tie str. 1 (know well) ²³	1			
tie str. 2 (get to know) ²³	-0.274***	1		
tie str. 3 (comm. freq.) ²³	0.517***	-0.048	1	
network overlap ²⁴	0.202***	-0.015	0.064***	1

However, already the descriptive statistics of network overlap and tie strength variables in Table 26 show that these two measures should be differentiated. Although network overlap exhibits moderate correlations with the main measure of tie strength (tie strength 1) and a low correlation with communication intensity (tie strength 3), these are merely correlations and not one-to-one relationships. However, if we map the information about the relationships between posters and users on the dimensions of weak vs. strong ties²⁵ and high vs. low network overlap²⁶, we find that the majority (68%) of the weak ties (80% of all ties) have low network overlap, whereas 13% have high network overlap. More importantly, the larger part (13%) of strong ties (19% of all ties) has low network overlap. Thus, we show that tie strength should

²³ - Because our measures of tie strength are dichotomous, we calculate tetrachoric correlations

²⁴ - Because network overlap is an interval rather than binary variable, we calculate the pointwise biserial correlation coefficients instead of the tetrachoric ones.

not be equated with network overlap and proceed to explore the relationships of these variables with information value in detail.

Table 26 **Tie Strength vs. Network Overlap**

		Tie Strength		
		weak	strong ²⁵	
Network overlap	high ²⁶	457 (12.89%)	217 (6.12%)	674 (19.01%)
	low	2412 (68.04%)	459 (12.95%)	2871 (80.99%)
		2869 (80.93%)	676 (19.07%)	3545(100%)

3.6 Estimation Results

The estimation results are presented in Table 27. Looking at estimates of the full model we find that tie strength positively and significantly (at 1% sig.) correlates with attention of users towards the information on SNS. We can thus empirically confirm Hypothesis C2.1. Furthermore, we see that the desire to develop the relationship also has a positive and equally significant (at 1% sig.), yet lower, impact on the valuation of information. We thus confirm hypothesis C2.2. Specifically, people prefer posts either from those they are already close with or want to become close to in the future. Controlling for these two measures of tie strength, the impact of self-reported communication frequency (tie str. 3) has no significant impact on attention towards information. Thus, we reject hypothesis C2.3. Note that this implies that self-reported communication intensity can be considered redundant as a measure of tie strength in the presence of self-reported closeness (tie str. 1). We find a negative and statistically significant relationship between network overlap and attention of users towards the post, indicating the presence of network redundancy and thereby confirming Hypothesis C2.4. We also find a small, but statistically significant (at 1%), curvature in this effect. This implies that the strength of this negative redundancy effect is marginally diminishing (i.e. a ‘half’ U-shaped relationship). The presence of ratings the information has received correlates positively and significantly (at 1% sig.) with user attention, whereas the presence of comments is not significant in attracting user attention. Thus, we can empirically support only the Hypothesis C2.5a. Finally, the frequency of sharing information by the user has a positive and significant impact on his attention towards information posted by others on SNS. We therefore also confirm hypothesis C2.6.

²⁵- According to table 2, strong ties constitute 19.07% of all ties, the rest 81% are weak ties.

²⁶- In order to estimate the cut-off point for the continuous variable of network overlap, we calculate its 81th percentile which is equal to 11.6%. This means that network overlap > 11.6% of any two users is considered high.

Table 27 Estimation Results of Model C2²⁷

	Full mo- del	Tie strength only	Network overlap only	Tie strength 1	Tie strength 2	Tie strength 3
tie str. 1 (know well)	1.02*** (0.128)	0.92*** (0.122)		0.957*** (0.121)		
tie str. 2 (get to know)	0.583*** (0.174)	0.537*** (0.173)			0.372*** (0.169)	
tie str. 3 (comm. freq.)	-0.008 (0.174)	-0.061 (0.174)				0.328** (0.167)
network overlap (% pts.)	-0.051*** (0.019)		-0.029* (0.019)	-0.045*** (0.012)	-0.033* (0.012)	-0.032** (0.018)
network overlap ² (% pts.)	0.001*** (0.0002)		0.001** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)
likes (1/0)	0.412*** (0.123)	0.457*** (0.122)	0.349*** (0.120)	0.411*** (0.123)	0.346*** (0.120)	0.347*** (0.121)
comments (1/0)	0.162 (0.111)	0.172 (0.111)	0.137 (0.109)	0.151 (0.111)	0.143 (0.109)	0.147 (0.110)
posting frequency	0.03*** (0.009)	0.03*** (0.009)	0.03*** (0.009)	0.03*** (0.009)	0.03*** (0.009)	0.03*** (0.009)
constant	-2.51*** (0.206)	-2.714*** (0.197)	2.274*** (0.198)	-2.449*** (0.204)	-2.305*** (0.199)	-2.27*** (0.198)
observations	3025 (121 respondents, 25 post evaluations each)					

As reported in Table 25, we find a statistically significant positive point biserial correlation (0.202, significant at 1%) between close ties (tie str. 1) and network overlap. That is, participants tend to have more network overlap with their close ties. The same however doesn't hold for those users would like to know better (tie str. 2). Due to the positive correlation, and conceptual ease of doing so, it is therefore quite natural to conflate tie strength with network overlap. Our results however indicate that when both are included together in a regression framework their effects are measured to be opposite. To further illustrate this point, the specifications have been reestimated first without network overlap (column 2 in Table 27) and then without tie strength (column 3 in Table 27). As tie strength and network overlap are correlated, if we exclude one of them, then a part of one variable will be included into the impact of the other and therefore we will not be able to discern the impact of each of them – known as omitted variable bias. If the

²⁷ - ***, **, * indicate that the estimated coefficient is statistically different from 0 at the 1%, 5% and 10% level respectively, n.s. indicates no statistical significance, n.a. – estimation not possible for this model. Bootstrapped (500 repetition) standard errors in parentheses, based on 121 clusters.

effects of these variables differ, this omission might make the coefficients smaller or render them insignificant because it pushes them back to 0. We see that in the first case the estimated coefficient on tie strength 1 goes from 1.02 to 0.92 while the one on tie strength 2 goes from 0.583 to 0.537. Similarly, if our measures of tie strength are excluded, the coefficients on network overlap become smaller in absolute value (from -0.051 to -0.029). Therefore, by excluding either tie strength or network overlap from the regression model, researchers run the risk of the omitted variable bias.

The last three columns of Table 27 give an idea of the biases which occur if one focuses only on a single measure of tie strength. Tie strength 1 – knowing the poster well – seems least affected by omitted variable bias and the estimated coefficient changes just a bit when the other two measures are excluded. However, because users tend to know posters they want to know better (tie str. 2) less well (see negative correlation between tie str. 1 and 2 in Table 25), the exclusion of tie strength 1 from the specification leads to a downward bias (by 0.2) in the estimated effect of tie strength 2. Finally, we note that only focusing on communication intensity (tie str. 3) as a measure of tie strength inflates this variable (see the coefficient estimate on tie str. 3 in the first column vs. in the last column of Table 27) and renders this variable significant. Thus, if the other two measures of tie strength are absent, communication intensity can serve as a proxy of tie strength. However, if one (or both) other measures are present, communication intensity on the network seems to be redundant as indicator of tie strength.

In terms of robustness the specifications have been estimated with robust standard errors derived through bootstrapping with 500 repetitions (Wooldridge, 2002). In addition, to assess the assumptions of independence between the ‘attention threshold’ μ (the random effect) and the explanatory variables in the random effects specification, we reestimate the full model via Fixed Effects and perform a Hausman test (Hausman 1978). Under the null hypothesis both of these specifications are properly specified and there are no systematic differences between the estimates. The resulting test statistic is Chi-squared distributed with six degrees of freedom and yields a value of 8.55 (p-value 0.286), which leads us not to reject the null hypothesis.

3.7 Discussion

In this study we measure the impact of network structure on the information value users derive from their networks. The first important contribution of our study is that we are able to measure the network structure of users in two ways: objectively by collecting the data about their network sizes and relative network overlap as well as subjectively by eliciting their underlying relationship with the people whose information they are asked to evaluate. Previously researchers had to invest a lot of effort to measure network structure of users, but SNS offer unprecedented environments in this respect. The inability to measure the network structure objectively has lead many researchers to equate tie strength with the redundancy of the network. Although we find that these two measures of network structure are correlated, we confirm that tie strength and network overlap have a diverging impact on the information value users derive from their network.

First of all, we explore the impact of several measures of network structure – underlying tie strength, desire to develop a relationship and intensity of communication on the network – on the attention of users to information on SNS. We show that the underlying closeness of the relationship is the best indicator of tie strength, which is also the main factor that leads users to pay attention to information on SNS: they prefer information from their stronger ties on the network as opposed to their weaker acquaintances. Although this finding is quite intuitive and has been supported in previous studies (cf. section B3.4), we show the persistence of this effect in all of the models we test. As stronger ties comprise only a smaller part of the individuals' networks, we additionally find that users are also interested in information about their weaker ties that they want to get to know better in the future. By providing constant information updates from these people, SNS environments provide good opportunities to develop these relationships.

However, the most widely used and objectively collectable communication intensity as a measure of tie strength did not have any impact on information value. This may be due to the fact that communication intensity on SNS is not necessarily an indicator of tie strength: in fact, users might prefer other channels to communicate with their close friends. Moreover, communication on SNS might be rather arbitrary, largely determined by other factors, such as the activity of the people on the network or the context of communication rather than tie strength. Although this result could also be due to the size of our sample: if two other measures of tie strength are excluded, communication intensity exhibits a high coefficient. Communication intensity on the network could thus also be used as a proxy of tie strength if other measures of tie strength are not available. However, if combined with the underlying closeness of the relationship, this measure of tie strength tends to be redundant.

Second, although tie strength is generally positively associated with the attention of users to information on SNS, network overlap has a negative impact. Specifically, we find the users evaluate the information from those friends with whom they have a lot of mutual friends negatively, compared to those with whom they have less of them. Presumably, the more mutual friends users have, the more redundant information they provide and therefore the less they are prone to pay attention to this information. Thus, our findings explain why people might be more interested in information from someone with whom they share less mutual friends, but a strong relationship (for example, a lover) as opposed to someone with whom they have more mutual friends, such as close friend. This is quite an interesting result, as on average mutual friends do not comprise a large part of the user's network (according to Figure 2, for 60% of the users these are on average just 5%). Moreover, the information about mutual friends is not directly available when users are evaluating information, but only if participants go directly to the profile of a user. That means that this effect is quite implicit, reflecting the subjective perception of the redundancy of the network that leads users to choose information from those less cohesive ties. We also found that the strength of the negative relationship between network overlap and information value diminishes as network overlap increases. In its turn this implies that past a certain network density, the marginal decrease in information value is negligible.

By distinguishing between network overlap and tie strength we are able to resolve the conflicting findings about the value of weak and strong ties as well as cohesive networks vs. those rich in structural holes on

information value, which has persisted since Granovetter (1973). Our study reveals that the benefits depend on the level of network analysis and confirms that both network structures can provide informational benefits to SNS users, only the sources of these benefits differ. Although tie strength is a more important determinant of information value than network overlap, on top of tie strength network overlap has a negative effect on the attention of users towards information. That is, considering two ties with similar tie strength, SNS users will be more interested in those users with whom they have less mutual friends. Thus we empirically confirm the theory of network redundancy proposed by Burt (1992). At the same time, considering two users with a similar number of mutual friends, users will be more interested in those with whom they have a stronger relationship. Thus we at the same time confirm the theory of Coleman (1988). Taken together, our results suggest that the most beneficial people in the network are those who balance between the least possible number of friends and the strongest possible tie strength. However, it is hard to have many such people in the network, as these two measures are correlated: with increasing tie strength, the number of mutual friends increases as well.

We also find support for the impact of social information on information value on SNS. The presence of ratings from other users tends to attract the attention of users and induce them to choose the posts with ratings. This is in line with the previous findings on the impact of ratings on information value. Interestingly, we do not find any significant association between the presence of comments and attention of users towards the information that is presented to them. This can be explained by the dual impact of comments on user attention: on the one hand, they might attract the attention of the user to the information that is shared, although on the other hand might create information overload, which is empirically confirmed in the section B3.4.

We also find support for the impact of the experience of using the medium on the attention users pay to information: it appears the more one posts oneself, the more one is interested in the information what others post. This might corroborate the channel expansion theory (cf. section A2.3) which proposes that the perceived usefulness of the medium increases as users gain familiarity with its functionality and understand for which purposes it can be best used and how.

4 Conclusion

Theoretical Contributions

A major contribution of this part of the dissertation is that we not only study the outcomes of network construction process, but also the dynamics of how the networks are formed. Overall, our study is the first attempt to investigate the network construction behavior of SNS users in a comprehensive manner. We find that tie strength is the primary heuristic users employ when they construct their network. That is, the stronger is the relationship with the person who is considered, the higher is the probability that the person will be included in the network. At the same time, the weaker is the tie, the more important are the secondary factors involved in the process of assessment. When assessing secondary factors, users engage in a cognitive calculus process of weighing the social capital gained and intrinsic benefits against the priva-

cy risks and the necessity of managing one's information once a contact is included into the network. Moreover, depending on the strength of the tie, different factors come into play when deciding to add others to their contact lists. For example, for weaker ties it is rather the self-presentation, whereas for stronger ties - the social capital benefits that motivate people to send a friendship request. Therefore, we observe similar results to the first part of the dissertation: tie strength seems to be the most important determinant of user behavior on SNS, by guiding not only their information processing strategies, but also the network construction behaviors.

However, in the second study we explore the concept of tie strength more elaborately and find that tie strength is not the only determinant of network structure that drives information value. We show the importance of empirically distinguishing between tie strength and network overlap as measures of network density when assessing how users value information on SNS. Due to the positive correlation between these two dimensions – one is indeed more likely to have more common friends with people that one knows well – and their opposing impact on information value that users derive from SNS, failure to differentiate between them empirically might lead to biased results. Thus we are able to partially explain the diverging views of the researchers on the value of strong and weak ties who have equated weak ties with low network redundancy (and vice versa) and argued for the value of less redundant networks. Indeed, less redundant networks may provide more benefits to its users, however, users are still more interested in information coming from their stronger ties on the network. We conclude that any empirical investigation into the value of information on networks needs to ensure that these two dimensions are addressed independently.

However, the most widely used and objectively collectable communication intensity as a measure of tie strength did not have any impact on information value. This may be due to the fact that communication intensity on SNS is not necessarily an indicator of tie strength: in fact, users might prefer other channels to communicate with their close friends. Moreover, communication on SNS might be rather arbitrary, largely determined by other factors, such as the activity of the people on the network or the context of communication rather than tie strength. Although this result could also be due to the size of our sample: if two other measures of tie strength are excluded, communication intensity exhibits a high coefficient. Communication intensity on the network could thus also be used as a proxy of tie strength if other measures of tie strength are not available. However, if combined with the underlying closeness of the relationship, this measure of tie strength tends to be redundant.

Methodological Implications

We are able to discern the distinct effects of network overlap and tie strength partially due to the design of the study. The application allows us to measure the network structure of users in two ways: objectively by collecting the data about their network sizes and relative network overlap as well as subjectively by eliciting their underlying relationship with the people whose information they are confronted with. Previously researchers had to invest a lot of effort to measure network structure of users, such as subjectively asking them about their network overlap and closeness to the people in it. SNS offer unique environments in this respect by allowing to objectively measure and analyze people's networks. Although we focus only on a

subset of available network structure – the overlap between the networks of two users, the application that we design offers unprecedented possibilities to analyze also the whole network of the user – an interesting venue for further research.

As opposed to the application introduced in section B3.2 of the dissertation, the application used in this study overcomes many of the methodological limitations. At first, it simulates the Newsfeed experience more fully, by providing users with 25 posts out of their Newsfeed and asks to select the ones they would pay attention to. Moreover, using this application we collect much more objective data that can hardly be assessed by users themselves (for example, network overlap) and combine it with the subjective evaluations of users of that information that is not available on the network (for example, tie strength). Therefore, as opposed to mainly perceived usage frequency tested in the model in section B3.4, here we are able to test the impact of objective usage frequency operationalized as active posting of information on information value. The advantage of using objective data is that due to various psychological distortions, users are not able to assess their behavior objectively. However, using perceived user's evaluations and comparing them to their objective behavior might also deliver valuable results.

Moreover, in this study we use methodological triangulation to analyse network construction behavior of individuals – by combining the insights gained in qualitative study and confirming them in an empirical analysis. As SNS is quite a new phenomenon with a lot of underexplored dynamics, it is important to conduct qualitative studies to generate hypotheses and propositions. What concerns the tested empirical models, we also check for their robustness by testing them with several different regression methodologies. Moreover, in order to empirically show the importance of distinguishing between network overlap and tie strength, we omit one of the variables from the tested models and observe that in one of the cases coefficients become insignificant. This could be expected, because when we omit one of the variables, part of the variance of the omitted variable is accounted for by the included one and as the effects of these variables are different, they push the variable back to 0.

Managerial Implications

From the perspective of an SNS provider, encouraging network expansion and connectivity between users is crucial for the success of viral marketing campaigns. Social ads, which take advantage of a user's friends as a basis for targeted advertising, constitute an important backbone of Facebook's business model. The mechanism of "social filtering" inherent on SNSs ensures that the information gets to its required recipient: As friends know the preferences of their friends better than any marketing tool, they can effectively direct marketing-relevant information to them. As it is coming from their personal connection, this information appears to be more trustworthy and, hence, more valuable for the recipient. In fact, irrespective of the level of familiarity, the information received on SNS is usually regarded as more targeted and personal, compared to other channels. Many companies are already exploiting this valuable feature of Facebook. For example: Amazon employs user profile information to provide product recommendations for gifts to friends (Fitzsimmons 2010c), retailers sort their products based on the amount of 'likes' on Facebook (Fitzsimmons 2010d), other companies are employing new technologies such as RFID chips (Fitzsimmons 2010a) or barcodes on mobile phones (Fitzsimmons 2010b) to enhance the spreading of

likes in real time. While “liking” promotes curiosity among users and thereby generates activity, profile information delivers valuable insights into customer base.

In turn, SNS providers are doing their utmost to connect users with each other, for example, by placing suggestions to add friends on the sidebar of the user’s profile or giving users an opportunity to import ‘friends’ from Email and IM contact lists (Smith 2009a). Our study provides valuable insights for the friends suggestion mechanism, which is currently based on friends of friends as well as the e-mail contacts of the user and her friends (Northrup 2009). As tie strength is the most important factor when deciding on connecting with friends, the providers should try to recommend those stronger ties to users who have joined an SNS. As tie strength is not manifested in the platform, such characteristics of friendship building as shared interests or common location, or such activities as being tagged in pictures, can be used to proxy it. Furthermore, connections to less familiar but ‘useful’ people who carry the potential of social capital benefits should be promoted based on employment and educational information.

Moreover, the insights of our study about the impact of network structure on information value can be used to improve information filtering algorithms. The fact that tie strength and network overlap have a diverging impact on user evaluations has to be considered when filtering information. Although network providers can not unambiguously determine the underlying tie strength of users, they can use such variables as user communication intensity to proxy it. The number of mutual friends, however, is recorded by the network and therefore could serve as one of the cues to filter information. That is if presented with information from two users with whom the participant communicates with the same frequency, information from the one with less mutual friends should be preferred.

Limitations

What concerns the first study on the network construction behavior, our sample size was small, compared to the population that we tried to study. Second, we relied on a student sample of mature Facebook users with slight male overrepresentation collected in the USA. Even though student samples are generally acceptable when the research question is “universalistic” in nature and involves psychological constructs (Kruglanski 1975), we strongly encourage validation of our findings with a more representative sample. Indeed, although Facebook originated in the USA as a campus network and students still represent a large proportion of its population, other demographic and social segments are gaining relevance as well (Smith 2009b). Fourth, the construct “expected relationship” was omitted from our quantitative study and should be included into future model validations to ensure model completeness.

What concerns the second study, most of the employed variables were binary which automatically limits the conclusions one can draw on the basis of the results. In terms of operationalization future research should therefore aim to nuance and expand the measurement of both the dependent variable as well as various measures of tie strength and network overlap. However, we feel that asking the respondents very granularly about every single piece of information and every contact would have resulted in respondent fatigue as they should evaluate 25 pieces of information.

D The Process of Social Capital Formation on Social Network Sites

In this part of the dissertation we unite the main concepts presented above – experience with using the medium, network structure and shared information – and explore their impact on the benefits of social capital. Specifically, we uncover the process of social capital formation, in which the different types of medium usage lead to the accumulation of shared information and network structure as the critical sources of social capital and through these impact the attainment of the benefits of social capital. Above the information value that we have explored in the previous section, here we complement the analysis with more tangible benefits of social capital, such as social support and participation.

1 Introduction

As SNSs are increasingly permeating our daily routines, policy-makers, parents, employers, scholars and even users are increasingly questioning: Does participation on SNS bring about any tangible benefits or are users just wasting their time on these networks? If SNS have little to offer in terms of tangible benefits, then the privacy risks they incur (Hogben 2007) call for public measures aiming to reduce their use. Therefore we turn to exploring the social capital that is derived from the individual's usage of SNS – referring to the value that arises from the individual's relationships with others (Bourdieu 1985) that SNS are able to effectively maintain (boyd and Ellison 2008).

The impact of Internet use on social capital is a highly debated topic. In the early decade researchers evidenced declining amounts of social capital due to growing social disconnectedness, alienation and technocratization caused by Internet use (Putnam 1995). Recent studies also show that SNS use may cause depression or breed envy and jealousy (Muisse et al. 2009; O'Keeffe 2011). However, other authors find evidence for the varying impact of the type of Internet use on social capital, where the negative effects are reversed if users are information- or communication oriented (Shah et al. 2001) – the goals people usually pursue on SNS (Joinson 2008). By allowing users to effectively maintain broad networks of geographically and socially dispersed acquaintances, SNS facilitate easy access to external resources of others (Ellison et al. 2007) and are even associated with reduced perceptions of loneliness (Burke et al. 2010). Until now, however, the role of SNS in the social capital formation process has not been fully uncovered.

Overall, even though existing studies provide a number of valuable insights, the questions of whether and how SNS facilitate formation of social capital remain unresolved. This is partly due to the absence of validated measurement instruments specifically developed to capture social capital outcomes in the novel context of SNS. Moreover, even if some authors provide evidence for social capital benefits resulting from general SNS use (e.g. Ellison et al. 2007), most neglect the process by which these benefits are gained. This is, however, very critical for the context of SNS, since not every type of use (e.g. Burke et al. 2010) and not any network (Granovetter 1973) possesses the same potential for value. Against this background, in this part of the dissertation we aim not only to develop the scales to measure social capital in

the context of SNS, but also empirically validate the process by which social capital is formed.

To accomplish our goals, we use methodological triangulation. First, following the overview of existing literature, we present the result of our qualitative analysis – the conceptual model of social capital formation on SNS. In the second step, the constructs are operationalized and a survey with a representative sample of Facebook users is conducted. Subsequent empirical validation of the model results in an array of theoretical and practical findings.

2 Theoretical Background

Social capital is a broader term used to refer to specific gains that can be obtained due to maintenance and development of relationships with others (Bourdieu 1985). Some authors (e.g. Portes 1998) stress the distinction between *outcomes* and *sources* of social capital. Typically explicit and often tangible *outcomes* of social capital refer to the productive utilization of the resources contained in the relationships with others, such as getting help or professional advice. In contrast, rather implicit and intangible *sources* reflect the ability to utilize the resources when needed, such as increased interconnectedness or a diversified network structure. In a circular model of socio-technical capital formation, Resnick (2001) makes this distinction clear: social capital outcomes, such as resource exchange or emotional support are viewed as side effects of previous activities, whereas communication paths, common knowledge, shared values, collective identity, obligations, norms and trust are the critical sources employed in this process.

Providing support for the source-outcome model of social capital formation, authors agree that *outcomes* of social capital largely depend on the underlying network structure (Williams 2006). More specifically, if the network is composed of a wide spectrum of weak ties or loose connections between individuals usually from different backgrounds, bridging social capital can be obtained – reflected in enhanced access to a broader set of material and informational resources, more opportunities and new perspectives (Granovetter 1973). If, however, the network consists mainly of strongly interconnected ties of the same type, individuals are likely to gain bonding social capital, or the benefits of social support (Williams 2006).

Concerning the impact of SNS use on social capital, most authors use the bridging and bonding categorization. Ellison et al. (2007) were the first to provide empirical evidence that the intensity of Facebook use is most positively associated with bridging, followed by maintained and then bonding social capital. Bridging role is rather attributed to SNS due to their enhanced capabilities and low costs of accumulating and maintaining weak ties (Donath and boyd 2004). Although Burke et al. 2010 find that the size of the individual network has a positive impact on bridging social capital, there is, in fact, a cap in the amount of friendships that can be effectively maintained on SNS (Tom Tong et al. 2008). In a later study, Ellison et al. (2011) prove the inverted u-shape relationship between the number of actual friends on SNS and social capital: the benefits diminish when networks go over 500 friends. Hence, a broad network structure alone is obviously not enough to generate the benefits of social capital on SNS.

Referring to bonding social capital, in the follow-up study Ellison et al. (2011) disprove that SNS use relates to the increases in this capital evidenced earlier. In fact, Vitak et al. (2011) show that although

beneficial for bridging, network growth is detrimental for bonding social capital. The larger the network, the less are the users able to maintain the quality of relationships within it and thus are constrained in sharing their concerns – the main prerogative of bonding social capital. Bonding social capital gains are more context-specific: Tufekci (2008) evidences that female SNS users are prone to gain more in terms of that capital, whereas Ellison et al. (2011) show that active communication and reciprocity are antecedent to obtaining emotional support on SNS. Taken together, more insights are needed to validate the process of social capital formation on SNS.

Determining the impact of distinct types of *SNS use* on social capital benefits might prove useful. Ellison et al. (2011) find that solely information-seeking behaviors are related to increases in bridging and bonding social capital, whereas strategies of initiating or maintaining relationships do not exert any significant impact on the benefits. Additionally, Burke et al. (2010) state that whereas active communication is associated with greater bonding social capital, increased passive consumption of content, in fact, reduces both types of social capital. Recognizing the importance in differentiating between forms of SNS use, we want to identify a full spectrum of activities that can be carried out on SNS and explore their distinct impact on the benefits of social capital.

Until now most authors operationalize social capital solely as bridging and bonding benefits (e.g. Ellison et al. 2007). This is mainly due to the fact that in order to measure social capital most authors use the scales developed by Williams (2006). We believe that that this distinction into bridging and bonding social capital may not be so critical in the context of SNS. As the networks of users usually include ties of different type, they can obtain emotional support also from less known people, or external resources (e.g. professional advice) – a traditional domain of weak ties – also from close friends. Against this background, in this study we distance ourselves from a traditional bridging/bonding classification and aim to identify the unique social capital benefits that can be gained on SNS as well as develop measurement scales for operationalization of this important construct.

Typically studies focus on estimating the influence of SNS use on social capital outcomes (e.g. Ellison et al. 2007) neglecting *sources* as an important intermediary stage of social capital formation. Summarizing the necessary sources for social capital formation, Nahapiet and Ghoshal (1998) point out the following dimensions: (i) *structural*, relating to the structure of the network; (ii) *relational*, reflecting the assets contained in the relationships such as trust; and (iii) *cognitive*, referring to attributes of the relationships, such as shared knowledge. While structural dimension replicates the availability of resources, the cognitive and relational dimensions describe the ability of the individual to obtain them. In our study we believe that the unique sources of social capital lie in the structure of the network and the shared information on the platform – which were extensively explored in the sections B and C of the dissertation. Following the framework of Nahapiet and Ghoshal (1998), network structure represents the structural property, whereas shared information - the relational and cognitive dimensions of social capital. Focusing on the sources along with the benefits allows us to uncover the process by which social capital is gained on SNS. Building on the insights from previous studies, extensive findings from qualitative research and

an empirical validation of the proposed conceptual model, in this part of the dissertation we aim to answer the following three research questions:

- (i) *What types of social capital benefits can be gained on SNS?*
- (ii) *What types of platform usage lead to which benefits of social capital?*
- (iii) *Which sources mediate the relationship between usage and benefits?*

3 Qualitative Study

3.1 Methodological Approach

In order to gain an in-depth understanding of the process of social capital formation on SNS a qualitative study was conducted in three steps. To obtain initial insights, in Summer of 2009 two focus groups were carried out. As students were probed with such questions as: ‘*What value do you obtain from SNS?*’ they experienced difficulties in identifying the “real” benefits of their SNS use, but rather centered on the unique ability to maintain relationships through SNS. Even if the interviewees obtained any “real” benefits, it was hard for them to recall them. Thus, in Fall of 2009 we conducted 8 participant observations, whereby respondents were asked to log-in and use their Facebook accounts, while answering such questions as: ‘*What value does this information bring to you? Why would you add this person to your network?*’, etc. This increased the range of possible social-capital related benefits. Finally, in Winter of 2010 we conducted six follow-up interviews of 30 minutes each, with the aim to find out how the benefits are gained on SNS. All of the eight observations and the six interviews were recorded, transcribed, and subsequently used for analysis with the software tool atlas.ti. All interviewees were between 21-25 years of age, had network ranges of 50-500 friends and were quite active users of Facebook spending from 10 minutes to several hours on the site daily.

The absence of systematic research on the process of social capital formation on SNS, urged us to use *Grounded Theory* to analyze the collected data. This research methodology enables structured analysis of large amounts of qualitative data. Through identification of critical concepts and exploring the underlying relationships between them we formulate a conceptual model of social capital formation on SNS. In our analysis, we follow the “Straussian” line of Grounded Theory (Strauss and Corbin 1998), which allows for prior knowledge on the subject matter and emphasizes the usage of a paradigm for axial coding.

The total of 14 interviews and participant observations were analyzed in three steps: open, axial and selective coding. During open coding initial concepts and their corresponding properties and dimensions were identified in a search process for patterns in the data. During axial coding the initial concepts were consolidated to form the overarching categories, and these in, turn, into coding families (actions – sources – benefits – context). This can be traced in Appendix 7: for each category the initial concepts that comprised it are listed. Application of the coding paradigm of Strauss and Corbin (1998) helped to uncover the relationships between the categories and thus formulate the conceptual model of social capital forma-

tion, depicted in Figure 20. The relative importance of each category in the overall conceptual model can be assessed by the number of times respondents mentioned the corresponding concepts presented in the frequency column in the Appendix 7. In the process of selective coding most relevant categories were identified.

3.2 Conceptual Model

Result of qualitative analysis - the conceptual model presented in Figure 20- describes the process of social capital formation on SNS. The benefits of social capital are gained through interactions on the network and the accumulation of the critical sources – network structure and shared information. The causal relationships indicate the general flow of the model: types of SNS use allow to accumulate the sources, which, in turn, help to attain the benefits of social capital. This implies that the benefits of social capital are possible, but not the necessary outcomes of SNS participation reflecting the model proposed by Resnick (2001). Sources are the necessary antecedents of social capital, but they also comprise the social capital itself by enabling the user to obtain certain benefits in the future. The frequency of the categories mentioned by participants as well as the lower level codes that comprised them are presented in Appendix 7, we notice that the model elements pertaining to the benefits were mentioned less frequently than the ones reflecting the sources of social capital, thus corroborating our proposition.

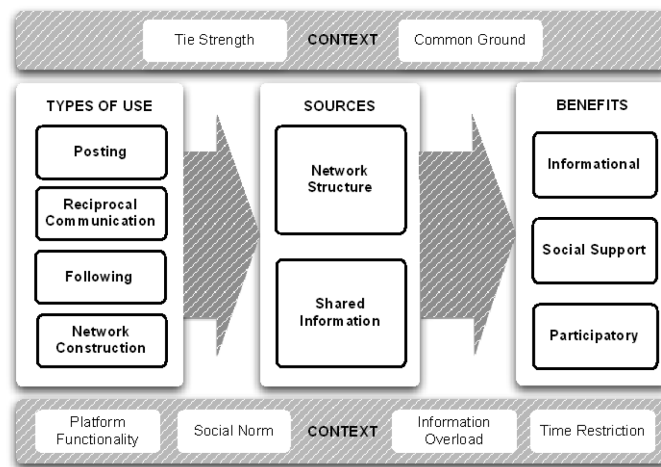


Figure 20 Conceptual Model of Social Capital Formation on SNS

Types of Use are ways in which users interact on the SNS platform (cf. Figure 1). Our qualitative analysis allowed us to differentiate four major types of SNS use: (i) *posting* some information; (ii) actively reacting to what others post in various *communication forms*; (iii) passively *following* what others post; and (iv) proactively constructing the *network* of friends. The types of use are the ways to gain experience with the communication medium in general and communication partners in particular, as discussed in section A2.3. We have also explored most of these types of use in the other parts of the dissertation: in section C2 we explored the motivations behind the network construction behavior, in section C3 we controlled for

the own posting frequency of users, whereas in section B3.5 we explored the impact of different forms of communication on information value. Through the interactions people exchange information and obtain knowledge about each others' interests and bring information to each other's attention in the future (Resnick 2001). Therefore, interactions constitute a means of exchanging information between the parties and largely determine when information flows and between which actors in the network. As people often accumulate social capital as a result of their daily interactions with friends, coworkers and strangers (Resnick 2001), the interactions on the SNS platform inevitably lead to the accumulation of the sources and benefits of social capital.

Sources of social capital are defined as productive resources that are inherent in social relations (Resnick 2001). In fact, the structure of the relations that people maintain on SNS and the information that flows between the people through interactions are the main sources of social capital (confirmed by the typology of ties depicted in Figure 1). These two sources of social capital— network structure and social connectedness – resemble the structural and cognitive dimensions of the framework proposed by Nahapiet and Ghoshal (1998). These sources constitute the main backbone of social capital, and they largely determine the benefits that can be gained as a result. They are rather passive and can be activated when needed.

Network Structure is defined as the structure and characteristics of ties in a network. Social relations often constitute information channels that reduce the amount of time and investment required to gather information (Burt 1992). Information benefits accrue to the individuals in three forms: accessing the piece of information and knowing how to use it, getting a more timely access to information and referring to other's expertise. As ties provide the channels for information exchange, their overall configuration constitutes an important determinant of social capital benefits (Nahapiet and Ghoshal 1998). It is largely believed that a sparse network with more redundant contacts provides more information benefits to its users (Burt 1992). A dense network is inefficient in the sense that it provides users with less diverse information for the same processing cost (Burt 1992). The results of the empirical model presented in section B3.4 show that strong ties can also deliver valuable information, in this study we focus more on the breadth and diversity of the ties in their impact on social capital benefits. Other authors also stress the aspect of diversity in users networks as social capital is created by bringing together information from disparate sources (Granovetter 1973).

The results of our qualitative study show that network structure has two important dimensions: the quantitative one, that is the number of ties in a network as well as the qualitative one – the diversity of these ties. As a result of SNS use, people are able to maintain connections to a much larger network than was possible traditional media: *“My network has increased immensely, and people who I know somehow happened to know that I'm on Facebook, so they want to keep in touch, they want to find out how I'm doing” (Interview Quotation (Q))*. At the same time, people are able to increase the diversity of the network by connecting to people from different backgrounds, various ages or social groups: *“The variety of people in my network has increased, for example there are so many family friends I know...and they might not always be my age...” (Q)*. We have already empirically shown that the strong ties result in information value, but as the results of qualitative study show that weak ties can also be sources of social

capital benefits, such as social support: *“Yeah, we're not that close, but I had her on my Facebook, and it was easy tell her: ‘Could you help me with that?’” (Q).*

Shared Information is defined as the informational resources that flow between the users on SNS through interactions on the platform. These resources might not be necessarily useful or users might not actively seek for them – which makes them different from the informational benefits of social capital that are discussed below. Information exchange occurs through interactions in social relations, whereby a certain shared meaning of the information is required (Nahapiet and Ghoshal 1998). In theory, shared meaning of information occurs through the existence of shared language and vocabulary as well as through sharing collective narrations – known as the cognitive dimension of social capital (Nahapiet and Ghoshal 1998). At the same time, the relational dimension of social capital refers to the qualities of the relationships that are maintained in the network, such as mutual trust, or shared norms (Nahapiet and Ghoshal 1998). For example, the more people trust each other, the more they are able to attain the benefits of social capital, such as emotional support. Our qualitative study reveals two dimensions of this source of social capital – the very information that is exchanged between the parties and the feeling of staying in touch and being connected to each other that emerges as a result, thus corroborating the dual structure reflecting the cognitive and relational dimensions of social capital by Nahapiet and Ghoshal (1998).

On the one hand, the ability to gain access to people and their information helps to activate the connections between individuals: *“I really like to learn what other people do: if they go on a trip, I like watching pictures... because I have a lot of friends in a really lot of places, and it's just that in this way I feel a bit closer to them” (Q).* Especially the shared meaning that is created through the interactions with each other can facilitate the feelings of connectedness and being close: *“I see when they communicate, and I can also take part if I wanted to. It's a way to stay in contact more, and somehow feel closer...” (Q).* But even without communication, the information that is shared on the network promotes the feeling of being connected to each other, being closer and staying in touch: *“You don't chat with them that much, you don't comment and vice-versa. But you know that when you want something from them, you can reach them through Facebook easily” (Q).* Indeed, sharing experiences and information as well as staying in touch are the main dimensions of the affective benefits and costs of mediated awareness questionnaire developed by Ijsselstein (2009) to measure not only content-oriented communication, but also connectedness-oriented one which is enabled through new media²⁸. Shared information plays a critical role in the attainment of the benefits of social capital, such as social support: *“And you always get the information... you know what others do and what they are up to and you can turn to them if you need it” (Q).*

Benefits are those tangible and intangible gains that accrue to the individual due to the relationships and interactions with others on SNS. Based on the insights from our qualitative study, we delineate three groups of benefits resulting from SNS use: informational, social support and participation, each of which

²⁸ - whereas the former is focused on the exchange of information, the latter is aimed at maintaining relationships and fostering sense of connectedness (Kuwabara 2002).

has several dimension to describe them. Benefits constitute a certain outcome – such as learning something new, participating in an event or getting help from someone. The structure of the benefits that we explore is also supported in the study by Resnick (2001), who mentions such benefits as information routing, resource exchange, emotional support and civic engagement as the main benefits of social capital.

Informational benefits of a network are centered around more broad access, faster timing, and referrals of information (Burt 1992), which can be enhanced by the unique features of SNS . Access refers to receiving a valuable piece of information and knowing who can use it. The information contained in the profiles as well as revealed through communication on SNS allows to determine who possesses the desired information and to whom this information can be useful. Although the Newsfeed does not have perfect algorithms for information filtering, users do not have to actively search for information, thus decreasing the costs of information access. Moreover, timing allows people to receive information from personal contacts earlier. Although this information may sometimes be subjective and incomplete, users can act on it, if they need it, either by learning more or passing it on to other contacts (Burt 2001). A user with a network rich in informational benefits has connections to those individuals where useful bits of information are likely to air and who provide a reliable source of information (Burt 1992). The difference between shared information and informational benefits lies in the fact that informational benefits should carry some explicit value above from learning the information itself. This value may lie in broadening one's horizon as a result of learning some new information, trying out something new or unexpected or learning some useful information from the friends in the network.

In our qualitative study the benefits emerged as having two dimensions: usefulness of information and non-redundancy of information exchanged on SNS. The result of getting useful information is manifested in the feeling of being informed: “on Facebook, I get a lot of useful information, and as a result I feel updated with what is going on around the world” (Q). The result of getting new non-redundant information is horizon broadening, which refers to increased range of things that someone knows about, has experienced or is able to do, which can occur on SNS: “It expands my outlook, especially due to the people whom one meets during vacations, who have different interests or live elsewhere and every person from another region with a different background deepens your knowledge about the people in particular and the world in general” (Q). As a result of information that one gets through SNS impulse to new ideas, trying out new things or learning from others related to all facets of life: “For example, someone who's listening to music has a Facebook plug-in, and I can see he's hearing a new band, so let me take a try...and thus, I discover new artists” (Q) – thus representing a more tangible benefit from SNS participation.

Social Support is defined as availability of people on whom one can rely and who can assist in times of need (Sarason et al. 1983). Differentiating between the ability of the network to provide social support and the actual provision of support, perceived social support is defined as the extent to which an individual believes that his/her needs for support, information and feedback are fulfilled (Procidano and Heller 1983). Therefore, social support is not only the perception that there is a sufficient number of others that to whom one can turn in times of need, but also as a degree of satisfaction with available support from

one's network (Sarason et al. 1983). There are several attempts to measure social support in literature: a scale developed by Procidano and Heller (1983), as well as scales by Sarason et al. (1983) and interpersonal support evaluation list by Cohen et al. (1985). In most of these scales one can recognize the items related to emotional support such as being there when one is feeling lonely or depressed, informational support in form of giving advice, or tangible support with, for example, providing accommodation, helping with appliances or giving a ride, etc. As we have already discussed the informational support that can be gained from the network and we want to differentiate this type of support from informational benefits that are especially conducive to SNS, in this part we focus on the instrumental and emotional dimensions of social support. These dimensions emerged as a result of our qualitative analysis.

Instrumental support is defined as the tangible value that the individuals can obtain from the access to the resources contained in the networks of others. These external resources usually refer to asking for help, such as accommodation during travel, putting in contact with someone or helping with finding a job. The structural network characteristics may lead to the provision of support (Procidano and Heller 1983). Our qualitative study shows that maintaining relationships with a broad range of individuals SNS provide users with easy access to the resources of others: *"I would say Facebook in a way helps you to build even your professional connections, like if I foresee somebody as a potential network in terms of business or professional, I would surely keep in touch with that person"* (Q). Interestingly, tangible benefits can generally be obtained from anyone in the contact list without any prerequisites of tie strength or intensive communication: *"If I need something banal, like accommodation in a different city, I would write to all of my friends on Facebook"* (Q).

Emotional Support refers to the emotional comfort by people in one's network. Interpersonal interactions may lead to emotional support (Feldman and Cohen 2000), as the participants of our study mentioned: *"If I need to talk to someone, I would post it on Facebook, because say its 10pm, so I wouldn't disturb my friends, and I'm too tired to go out..."* (Q). In traditional contexts emotional support is usually provided by stronger ties, as people who know and trust each other are more likely to share personal information with each other and feel supported through these interactions (Williams 2006, Resnick 2001). However, on SNS such type of support can be obtained from anyone in the network: *"I was unhappy because of my boyfriend and when many people wrote to me it made me feel much better, and I was surprised that support came also from people who were my distant acquaintances or the ones who I know just on Facebook..."* (Q). The fact that on SNS any type of benefit can be obtained from anyone in the network makes a distinction into bridging and bonding social capital less critical for SNS context.

Participation Many researchers have defined social capital as engagement in political and civic activities, the main elements of which are participation in electoral activities, working for political parties, working for the community or attending a protest (Verba et al. 1995, Conway 1985). The impact of the Internet on offline participation has been a hotly debated issue among researchers. Some argued that as any new media, simply because of the inelasticity of time, Internet reduces interpersonal interaction and communication (Nie, 2001) as well as leads to a drastic reduction in political and civic engagement (Putnam 1995). Others state that Internet, inversely, creates new forms of online interaction and enhances

offline relationships (Wellman et.al, 2001). In fact, the intensity of SNS use positively relates with civic engagement and political participation, probably due to the fact that SNS can connect activists with similar goals and create awareness about critical issues (Valenzuela et al. 2009). The same might occur on SNS: as on these networks people are able to maintain large and diverse networks as well as form productive relations even more conveniently (Resnick 2001). As a result, there is a higher probability that there will be someone in the network with similar interests or someone from whom one can learn about an event and take part in it.

We define participation on a broader level as engagement in organizations, participation in offline events as well as organization of offline meetings with friends. Our qualitative study recognizes two dimensions of participation as a result of interactions on SNS and maintenance of relationships: involvement in offline social activities as well as offline meetings with friends. Contrary to the findings of Putnam (1995), we find that, users tend to take part in more and more diversified events: *“He was from our school and when I saw him in the library, I added him on Facebook. And then, I got a thread, an invitation for going to an exhibition I did not know about along with a lot of people” (Q)*. On the other hand, contrary to the propositions developed by Nie (2001) about decrease in offline interactions due to Internet use, we find that due to the increased interactions on SNS, users arrange to meet their friends more frequently in person: *“With those people you usually communicate everyday, and when there is a party going on, you simply send an invitation to all those people, or just to do something together, watch a movie” (Q)* and thus enhance their participatory capital.

The social capital benefits identified in our qualitative study to some extent resemble the dimensions of the bridging and bonding social capital benefits outlined by Williams (2006). For example, horizon broadening is one of the dimensions of the bridging social capital, whereas emotional support – of the bonding social capital initially recognized by Williams (2006). At the same time, other dimensions singled out by Williams (2006) emerged as less relevant for the SNS context: for example, ability to mobilize solidarity or out-group antagonism. This is due to the fact that Williams (2006) was developing scales to measure social capital resulting from Internet use that is multi-purposeful. The advantage of our framework is that the identified dimensions of social capital benefits are tailored to the specifics of SNS context and are the most salient ones elicited directly from SNS users. Moreover, Williams (2006) does not differentiate between sources and benefits of social capital: his bridging scale includes both contact to a broader range of people and the benefit of linkage to external assets. Our model shows that the network structure is, in fact, an antecedent to such social capital outcomes.

Context

As social capital is rooted in the relationships between users, the model recognizes that tie strength and common ground are the context in which the accumulation of individual social capital takes place. These features can accelerate the sources of social capital formation. Although we show that emotional support or also tangible help can be also obtained from weak ties, strong ties are usually the first ones from whom help is sought: *“I mean of course I first check with my close friends, but if they are not able to help me, I*

can easily turn to others in my network” (Q). At the same time, if individuals share common ground, they are better able to interpret the information that is shared and generate the necessary meaning to obtain social capital benefits: *“I pay attention to his information, because he is doing sailing and I am very much interested in it as he is more advanced and I can learn from him...” (Q).*

Moreover, the process of social capital formation can be accelerated or constrained by certain intervening conditions – describing the broader structural context in which social capital is formed. The intervening conditions of the model are either such general structural factors as time restriction and perception of information overload; or specifically relating to peculiarities of SNS as communication medium: platform functionality and social norm. For example, SNS functionality allows users to effectively maintain these broad networks and thus gain benefits of social capital: *“I just have all these people in my network, and maybe one day I would need to contact them...” (Q).*

4 Empirical Study

4.1 Study Design

The survey was distributed through student and alumni mailing lists of several universities. In total, 350 people completed the survey. After removing incomplete and unusable answers, 253 observations were left for analysis. Our sample consists of 45% male and 55% female respondents. Most respondents - 70% of the sample - reported having a college degree, and only 25% are students. Both mean and median age of the respondents is 25, with the spread of 21 – 44 years. Considering that 70% of Facebook users are between 18 and 44 years of age (Morrison 2010) and 55.60% of Facebook users are female (Eldon 2010), our sample is representative for a significant part of Facebook population. The mean/median size of a friend list of our respondents constitutes 259/200 friends respectively, which is higher than an average of 130 reported by Facebook (2011). 65% of the respondents have been using Facebook for more than 2 years and 80% of the respondents spend more than 30 min on Facebook daily. All in all, the sample represents the largest group of Facebook users – mature active users.

The items we used for the study can be traced in Appendix 8 (items related to usage of the medium) and Appendix 9 (items related to the benefits). All constructs in the study involved multiple items and were modeled reflectively. In developing the items we relied on pretested scales, where possible. Items relating to the benefits of social capital were adopted from Williams (2006), social support extended with items of Procidano and Heller (1983), shared information was operationalized similar to Ijsselstein et al. (2009). Items related to actions were for the most part self-developed. Results of the qualitative study including exact wording of the interviewees were often used as a basis for construct operationalization. The initial survey items were tested during two one-on-one sessions, where respondent was filling out the survey in the presence of the interviewer and was encouraged to evaluate the understandability of the survey items. After these sessions, survey items were slightly modified. All constructs related to usage of the medium were anchored on a five-point Likert scale (1= almost never; 5= almost every day): 4 items in the posting

dimension (P1-P4), 5 items in the communication (C1-C5), 4 items in following (F1-F4) and 5 items in the network construction dimension (N1-N5) (see Appendix 8). All other constructs relating to benefits and sources of social capital were measured on a seven-point Likert scale.

4.2 Identification of Dimensions

As we have largely adopted or developed the items anew for most of the constructs we use in the study, we first need to carry out an exploratory factor analysis (EFA) to examine whether the structure of the constructs identified in the qualitative study would also hold in the factor groups identified by EFA. A principal components method with a varimax rotation was performed on the collected data using SPSS 20.0. Varimax rotation was chosen due to its ability to render interpretable results. Taking into account the possible correlations between the analysed factors, we have also crosschecked our results using a direct oblimin rotation, which yielded equivalent factor structure. Exploratory factor analysis is done separately for the actions and for the sources/benefits of social capital.

Actions

In the first step, we examine whether the structure of the four participation types identified in the qualitative study would also hold in the factor groups identified by EFA. As a solution, 5 factors with eigenvalues higher than 1 were extracted. The results are presented in Appendix 8. All factor loadings exceeding the threshold of 0.4 were considered meaningful (Hair et al. 1998). Contrary to expectations, more factors than initially hypothesized were extracted and some of the items did not load on the anticipated factors. As a result, new dimensions have emerged and the typology of the recognized participation patterns had to be adjusted. All items in the newly identified factors fulfilled the narrow definition of “factor purity” suggested by Saucier (1994). Based on this criterion, C3 was removed, as it loaded highly on two factors and it was hard to meaningfully discern it from any of them.

The first factor – *active participation* – combines most items that belonged to the categories posting and communication. It appears that users do not distinguish between posting and communicating, as active participation in essence includes both of these activities. The second factor – *passive following* – relates to the activities of simply following content posted by others. The third factor – *social browsing* – refers to more targeted search of information through browsing the profiles of others. Contrary to expectations, SNS users make a distinction between passively consuming certain information and proactively searching for it. The latter factor, in fact, resembles the social browsing identified by Lampe (2006) or the information-seeking behaviours in the study of Ellison et al. (2011). The fourth factor – *network construction* – is directed at proactive construction of ones’ network which we have extensively explored in section C2. The fifth factor refers to private communication. This factor was not considered for analysis, as its Cronbach’s alpha was too low (0.5) and thus the corresponding items C4 and C5 were removed from the final scale. The factor analysis was repeated after the above mentioned items were deleted and the result yielded an equivalent solution to the one presented in Appendix 8.

Benefits and Sources of Social Capital

In addition, we also conducted EFA for the survey items relating to benefits and sources of social capital in order to test whether these represent distinct factors as the qualitative study proposed. Again, a principal components method with a varimax rotation was performed to check if the category structure was also reflected in the extracted factor groups. The results are presented in Appendix 9. As expected, 5 factors with eigenvalues higher than 1 were extracted with all indicators loading well on the latent constructs they were supposed to measure – three relating to social capital benefits and two to sources. All factor loadings exceeded the threshold level of 0.4 (Hair et al. 1998). Only one factor did not fulfil the narrow definition of “factor purity” suggested by Saucier (1994): item OP1 loaded on both participation (.639) and information benefits (.436). This is probably due to the case that users take part in more events, because they learn about them from their friends on SNS. Considering that the extracted factors should be interpreted in the light of theory and not by arbitrary cut-off levels (Hair et al. 1998), these indicators were integrated as items of the constructs they were initially intended to measure.

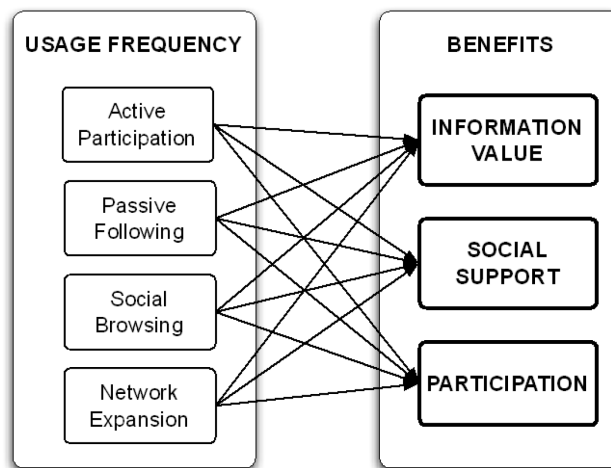


Figure 21 **Research Model D1 (direct)**

4.3 Research Models and Hypotheses

In this section we aim to empirically test the proposed conceptual model of social capital formation on SNS that we have derived in the qualitative study as well as validated in the Exploratory factor analysis. In line with former studies (Ellison et al. 2007; Vitak et al. 2011), we aim to explore the direct impact of different types of SNS use on the identified social capital benefits. We differentiate between various types of SNS usage, as social capital benefits are contingent on the activities users perform on SNS (Burke et al. 2010; Ellison et al. 2011). Thus, the direct model presented Figure 21 examines the relationships between the identified types of SNS use – active participation, passive following, social browsing and network construction on the identified benefits of social capital – information value, social support and participation. We have already explored the motivations behind the network construction behaviors or users in section C3 and here we would like to explore how it is related to various forms of social capital benefits along with other possible types of network use. At the same time, in section B of this dissertation

we were extensively exploring the factors that lead to information value – and here we complete this analysis with different types of social capital benefits.

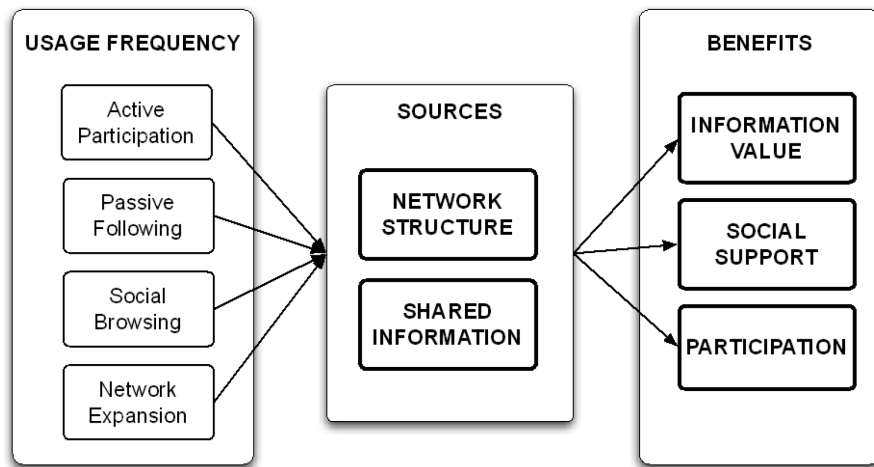


Figure 22 **Research model D2 (mediated)**

In the second stage, we validate the mediating role of the sources of social capital - network structure and shared information – that has vividly emerged in our qualitative analysis and is captured in the 3-tier conceptual model in Figure 20. Indeed, a broader and more diversified network structure has been found to be beneficial for bridging social capital (Ellison et al. 2011). In the section C3 of this dissertation we show that network structure plays an important role: people find that information from their stronger ties on the network is more valuable, although network overlap negatively impacts value perceptions. In this study we focus on the diversity of the network and explore its impact on the possible social capital benefits. Moreover, previous theoretical findings suggest that shared information is the fabric that keeps the relationships alive and allows people to feel closer to each other (Köbler et al. 2010). In the section B of this dissertation we explore the properties of information that is exchanged on SNS and in this study want to explore its impact on various types of social capital benefits. Against this background, in the mediated model depicted in Figure 22 we explore the role of network structure and shared information as mediators of the relationship between the identified types of SNS use and the respective outcomes of social capital.

4.4 Estimation Results

The empirical validation of the proposed conceptual model depicted in Figure 20 comprised two steps. First, the direct effect of the four types of SNS use on the benefits of social capital: (i) information value, (ii) social support and (iii) participation was tested (cf Figure 21). Second, the mediating effect of the sources of social capital - network structure and shared information – was tested for the relationship between actions and respective benefits (cf Figure 22).

Partial Least Squares (PLS) approach was used to evaluate the models. Indeed, PLS is particularly suited for testing and validating exploratory models such as the proposed conceptual model of social capital

formation (Henseler et al. 2009; Fornell and Bookstein 1982). As suggested by Chin (1998) and Ringle (2004), first the measurement and then the structural model was evaluated for both the direct and mediated model. Since all constructs were modeled as reflective, only reflective measurement evaluations were used. All calculations were carried out using SmartPLS 2.0 (Ringle et al. 2005).

Table 28 **Convergent Validity of Constructs in Models D1 and D2**

Construct		AVE		Composite Reliability		Cronbach's Alpha
Model		D2	D1	D2	D1	
ACTIONS	Active Participation	0.72	0.72	0.94	0.94	0.92
	Passive Following	0.68	0.68	0.86	0.86	0.76
	Network Construction	0.63	0.63	0.84	0.84	0.71
	Social Browsing	0.66	0.65	0.85	0.85	0.76
SOURCES	Shared Information	0.64	-	0.87	-	0.81
	Network Structure	0.66	-	0.91	-	0.87
BENEFITS	Informational	0.64	0.64	0.88	0.88	0.81
	Participation	0.63	0.63	0.87	0.87	0.81
	Social Support	0.61	0.60	0.86	0.86	0.79
	Benchmark	.5²⁹		.6³⁰		.7³¹

Evaluation of the Measurement Models

In order to evaluate our measurement models, internal consistency, convergent and discriminant validity of the measured constructs were assessed for the direct and mediated model. The results presented in Table 28 show that all of the measured indicators meet their required criteria. Internal consistency is assured (Nunnally 1978), as Cronbach's Alpha for all latent constructs is above 0.7. Convergent validity can be assessed by exploring indicator reliability, composite reliability, and average variance extracted. All indicators meet the required cut-off level of 0.7 (Hulland 1999), except for: items SS3 with a loading of 0.666 in the direct model. As only indicators with factor loadings less than 0.4 should be eliminated (Homburg and Giering 1996), no indicator was excluded from any model and we can say that indicator reliability is assured. Second, composite reliability (CR) of all latent constructs is above 0.8, which exceeds the minimum required threshold of 0.6 (Ringle 2004; Homburg and Baumgartner 1995). Average Variance Extracted (AVE) of all latent variables in all 8 tested models is bigger than 0.5 (Fornell and

²⁹ - AVE threshold of 0.5 (Fornell and Larcker 1981)

³⁰ - Composite Reliability (CR) threshold of 0.6 (Ringle 2004)

³¹ - Cronbach's alpha (CA) threshold of 0.7 based on Nunnally 1978

Larcker 1981). Taken together, convergent validity can be assumed for both the direct and the mediated model.

Table 29 **Discriminant Validity of Constructs in Model D2**³²

Construct	AP	PF	NC	SB	SI	NS	I	P	S
Active Participation (AP)	0.85								
Passive Following (PF)	0.52	0.82							
Network Construction (NC)	0.19	0.16	0.79						
Social Browsing (SB)	0.30	0.32	0.33	0.81					
Shared Information (SI)	0.44	0.49	0.11	0.31	0.8				
Network Structure (NS)	0.35	0.27	0.36	0.17	0.45	0.81			
Informational (I)	0.36	0.41	0.19	0.23	0.55	0.56	0.8		
Participation (P)	0.36	0.23	0.19	0.17	0.47	0.38	0.49	0.79	
Social Support (S)	0.46	0.26	0.22	0.17	0.40	0.40	0.45	0.47	0.78

Discriminant validity was assessed by ensuring that the square root of the AVE for any latent variable is bigger than the correlation between this variable with all other latent variables in the model, as recommended by Fornell and Larcker (1981). The results of the calculations for the mediated model presented in Table 29 reveal that no correlation between two variables was close to the square root of the AVE. Hence, discriminant validity can be assumed. We also notice that the correlations between all our explored variables are moderate.

Evaluation of the Structural Models

Since PLS does not generate an overall goodness of fit index, model validity is assessed by examining the structural paths and R^2 values. R^2 measures the share of the variance of the latent endogenous variable which is explained by the latent exogenous variables in the model. The endogenous variables are the social capital benefits, whereas the exogenous ones are the actions and, in the mediated model, the sources of social capital. For the purposes of explorative research, R^2 is considered sufficient, when it is above .33, although accepted are also R^2 of over .19 (Hansman and Ringle 2005). In the next step, the significance of the path coefficients based on a bootstrapping procedure was evaluated. The bootstrapping was carried out with 200 samples.

As mentioned above, first, the direct impact of various types of SNS use on the benefits of social capital was tested. The results presented in Table 30 reveal that active participation is significantly positively associated with all three types of social capital benefits. Judging by the absolute value of the coefficient, it is especially important for the social support, followed by participatory and only after that informational

³² - Square Root of AVE on the diagonal and Correlation between Latent Constructs

benefits. Passive following is significantly positively related to informational benefits and seems to be even more important for this type of social capital than active participation. Interestingly, social browsing is not directly related to any type of benefits on SNS. Successful network construction behaviors result in the benefits of social support and participation. This could be expected, as one can only obtain these benefits if one has the appropriate structure of the network. The R^2 of participatory benefits at 0.15 indicates minimal explanatory power of the model (Falk and Miller 1992), whereas the R^2 of social support and informational benefits (at 24.1% and 21.7%, respectively) are considered acceptable (Hansman and Ringle 2005).

Table 30 Estimation Results of the Direct Model (D1)³³

Actions/Benefits	Social Support	Informational Benefits	Participatory Benefits
Active Participation	0.431*** (0.057)	0.178*** (0.078)	0.314*** (0.067)
Passive Following	0.016 (0.067)	0.287*** (0.069)	0.04 (0.072)
Social Browsing	0.004 (0.058)	0.07 (0.063)	0.028 (0.074)
Network Construction	0.151** (0.067)	0.097 (0.064)	0.127** (0.059)
R²	24.1%	21.7%	15%

In the second step, the mediation variables – shared information and network structure were included. Judging by the results presented in Table 31 we observe several interesting effects. First, we note the factors that lead to the formation of the sources of social capital. Shared information is accumulated as a result of active participation, passive following and social browsing (which are positively and significantly related with it). The fact that social browsing is positively associated with shared information, but does not lead to any benefits of social capital highlights the importance of differentiating between benefits and sources of social capital: although it does not have a direct effect on the benefits, it impacts the benefits through the sources of social capital. At the same time, network structure is a result of active participation in the network and network construction behaviors. Both network structure and shared information are positively and significantly associated with all the benefits of social capital. Judging by the absolute values of the coefficients presented in Table 31, we notice that network structure is especially important for information benefits, whereas shared information – for the participatory benefits of social capital.

Table 31 Estimation Results of the Mediated Model (D2)³³

³³ - Path coefficient (standard error), significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

	Shared Informa- tion	Network Structure	Social Support	Informa-tion Value	Participa- tion
Active Participation	0.225*** (0.059)	0.250*** (0.063)	0.325*** (0.062)	0.002 (0.061)	0.185*** (0.066)
Passive Following	0.340*** (0.074)	0.108 (0.068)	-0.065 (0.062)	0.158** (0.069)	-0.09 (0.071)
Social Browsing	0.139*** (0.056)	-0.043 (0.061)	-0.03 (0.053)	-0.019 (0.047)	-0.015 (0.073)
Network Construction	-0.023 (0.063)	0.318*** (0.056)	0.084 (0.065)	-0.019 (0.047)	0.073 (0.067)
Network Structure			0.189*** (0.067)	0.390*** (0.058)	0.161** (0.073)
Shared Information			0.214*** (0.069)	0.291*** (0.067)	0.361*** (0.07)
Rsquared	30.5%	22.1%	30.3%	45.3%	28.9%

Second, we explore the mediation effects created by the introduction of the sources of social capital. The mediation was present in the relationship between an action and a benefit if the two links were significant: (i) between an action and a respective mediator; and (ii) between a mediator and a respective benefit. Once these criteria were fulfilled, mediation was additionally evaluated via the Sobel (1982) test, as recommended by Baron and Kenny (1986). First, some direct links between types of SNS use and benefits become insignificant, specifically: the relationship between active participation and information value, as well as network construction and both social support and participatory benefits. Combined with the results of the Sobel test in Table 32 it is clear that these relationships are fully mediated by the sources of social capital – shared information and network structure. All the other coefficients of the direct connection between actions and benefits of social capital become smaller in absolute value, specifically: active participation with both social support and participatory benefits, as well as the relationship of passive following with information value. Combined with the results of the Sobel test (Table 32), we conclude that shared information and network structure are the partial mediators of these relationships. It is obviously rather these sources of social capital that lead to the benefits of social capital than the activities on SNS.

Once we add the sources of social capital to our models we notice that the explanatory power of our model increases considerably: the types of SNS use together with the sources of social capital explain 30% of the social support, 28.9% of participation benefits, and 45.3% of information value, which is at or close to the sufficient benchmark (Hansman and Ringle 2005). Additionally, we evaluate the effect size to determine the impact of each the mediators on the overall explanatory power of the model. The effect size is calculated by comparing the R^2 of the dependent variable with and without the presence of each independent variable (Chin 1998), whereby effect size of over 0.02 is considered small and over 0.15 – medium

(Cohen 1988). The results of effect size calculations are presented in Table 32. These results reveal that just one of the mediators does not increase the explanatory power of the models to a large extent. The most notable effect is the impact of network structure on the informational benefits. This might be due to the fact that shared information and network structure alone are not enough to cause the necessary increase in explanatory power, but jointly they allow to explain more of the variance of the social capital benefits.

Table 32 Effect sizes and Sobel Test Statistics for Model Mediators

Model	Mediator	Effect Size	Predictor	Sobel Test p-values (two-tailed)
Participation	Shared Information	0.08	Active participation	3.06***
			Passive following	3.43***
			Social browsing	2.23**
	Network Structure	0.02	Active participation	1.92**
			Network Construction	2.05**
Informational	Shared Information	0.05	Active participation	2.86***
			Passive following	3.15***
			Social Browsing	2.15**
	Network Structure	0.10	Active participation	3.42***
			Network Construction	2.46***
Social Support	Shared Information	0.02	Active participation	2.4**
			Passive following	2.57***
			Social browsing	1.94**
	Network Structure	0.02	Active participation	2.29**
			Network construction	2.52***

4.5 Discussion

Our study provides an array of theoretical contributions. First, we identified in the qualitative analysis and empirically verified three unique types of social capital benefits for the context of SNS. Empirical validation of the developed measurement scales for these constructs through exploratory factor analysis represents an important methodological contribution of our study. Indeed, in the past authors (e.g. Ellison et al. 2007) have mainly relied on the bridging and bonding scales proposed by Williams (2006), which were developed for the general Internet context. Some of the items in our proposed scale are similar to Williams (2006), but bear the advantage of being tailored to the specifics of SNS context. For example, we delineate participation as a specific benefit resulting from SNS use. Moreover, our scales depart from the usual bridging-bonding categorization as well as focus solely on tangible outcomes of social capital, while treating sources as a separate antecedent construct. Taken together, the developed framework and

accompanied measurement scales are likely to provide significant support for future scholars studying social capital formation on SNS.

Furthermore, our study provides a validated categorization of types of SNS use. Previously authors focused only on one segment of SNS participation, distinguishing between active vs. passive uses or between social searching vs. social browsing (Lampe et al. 2006; Ellison et al. 2011). Closing this gap, our categorization accounts for all possible activities on SNS, and provides validated scales for the measurement of distinct SNS activities. Our study also reveals which types of SNS use lead to which benefits of social capital. We find that whereas active participation is beneficial for all types of social capital, a diversified network structure is rather associated with social support and increased participation and passive following leads to informational benefits. Surprisingly, in our study social browsing - which is a directed and more goal-oriented strategy of searching for information about others does not lead to any social capital benefits, whereas Ellison et al. (2011) recognize it as the most important means to obtain social capital. We explain this by the fact that social information gained in the process of browsing may lead users to experience envy (Muise et al. 2009) or frustration (Koroleva et al. 2010) and thus potential to extract social capital can get lost. It maybe also due to the case that people are searching information just for the sake of it and not to obtain any tangible benefits. This is corroborated by the fact that we find that social browsing leads to the accumulation of shared information, and through this source of social capital, may impact the social capital benefits.

The most interesting finding of our study is that actions alone are not enough to explain the process of social capital formation on SNS. By introducing shared information and network structure as mediators into the tested models, we show the critical role of these sources in the process of social capital formation. It appears that, while certain actions allow users to expand and diversify their network and lead to accumulation of more information about the contacts in their network, these sources, in turn, are mainly responsible for the attainment of the benefits of social capital. Thus we confirm the model of Resnick (2001) for the case of SNS: social capital benefits are indeed only side effects of participation, whereas the broader social capital is centered around the qualitative and quantitative properties of the individual network. This can be illustrated with a simple example: if a user has never obtained any tangible help from others in her network, does it mean she has no social capital? The answer is no, because if she possesses the desirable network structure and has information about who possesses which resources and has what expertise, tangible help can be obtained anytime.

Even though network structure has been recognized as important prerequisite of social capital gains in previous studies (Ellison et al. 2011), our study is the first one to show that a diversified network structure is beneficial for any type of benefit – informational benefits, social support and participation. Diversified network structure is important to gain non-redundant information, learn about new events and undertake activities with people with whom one shares interests, but does not communicate on a regular basis. A broad structure of the network is also beneficial for social support: the more people one has in the network, the more probable it is that one of them will be there in times of need or has had a similar experience and can share it and thus provide social support. Shared information is important in the sense that it

provides the necessary fabric to trigger interactions, as a result of which people can arrange to meet each other or obtain emotional and social support. At the same time, based on the information that is shared on the network the user is always updated about who knows what and has which capabilities, thus stressing the importance of transactive memory recognized by Borgatti (2009). Thus, user can act upon this information if needed and obtain tangible benefits, advice or take part in events.

Taken together, our study uncovers the specific process of social capital formation for each of the identified social capital benefits. For example, for participation, shared information is critical, whereas for informational benefits, a diversified network structure is more important. Furthermore, to gain social support active participation is of essence. Indeed, by passively viewing the information posted by others, one is more likely to feel irritated rather than supported by friends (Sachoff 2011). Emotional comfort requires reciprocity – and already several messages may be enough to generate the feeling of support. Finally, in contrast to grim perspectives outlined by Putnam (1995), our study confirms the possibility of SNS to increase offline participation. The combination of proactive network construction and shared information urges users to arrange to meet their friends more often and take part in more events than they would do otherwise. This can be of use to SNS users, policy-makers or network providers to better understand how SNS function.

5 Conclusion

Coming back to the research questions, in the paper we identified three types of social capital benefits that can be gained as a result of SNS participation. Furthermore, we determined which participation patterns lead to which benefits, as well as empirically proved the importance of the sources of social capital in the process of social capital formation. We showed that the structure and qualities of the individual social network are the most crucial determinants of social capital benefits. That is, if individuals want to gain from SNS usage, they have to concentrate their efforts on constructing a broad and diversified network as well as invest time into maintaining their relationships with others.

Theoretical Implications

On the theoretical side this part of the dissertation combines the concepts that were explored in the two previous parts – and which are reflected in the generic model depicted in Figure 4. That is, we study different types of SNS use (apart from studying general use or only separate forms of use) as well as different types of social capital benefits (apart from information value that was the focus of the two previous parts). Moreover, we show how these elements interact in the process of social capital formation, where information (which was the focus of section B) and network structure (main argument of section C) are the main sources that lead to the benefits of social capital. We find that active participation through sharing information and commenting may directly result in the benefits of social capital, whereas other types of use rather result in the accumulation of sources and through them lead to the benefits of social capital. That is, passive following and more targeted browsing of the information posted by others leads to the accumulation of shared information, which if needed may result in participatory or informational benefits.

At the same time network construction behaviors (which we extensively explored in section C2) lead to the accumulation of the diversified network structure, which results in informational benefits and social support. Thus, we empirically show the process of social capital formation on SNS which can be used by scholars as well as practitioners.

Practical Implications

When it comes to managerial implications, results of our study suggest that SNS providers should urge users to communicate more actively and invest into optimizing their friend lists. These strategies will allow users to gain more benefits and, hence, experience more satisfaction with their SNS activities. Moreover, network providers can optimize information filtering algorithms to provide users with the necessary and relevant information at all times to promote the sharing of information and avoid information overload, which can be detrimental to social capital.

At the same time, our study shows that SNS participation does result in benefits for its users, as opposed to grim trends of technocratization and alienation outlined by Putnam (1995). In fact, we show that as a result of increased communication on SNS, people engage in offline activities and thus SNS have a potential to become catalyzer also of civic and political actions. Indeed, SNS are known to be main motivators of different political movements, protesting actions, or mobilizers of masses in uprisings against dictator regimes. Also the censorship of SNS in some of the countries, such as Belarus, or ban of Facebook in China, illustrate that these networks have a potential for creation of political and civic action. At the same time, the fact that SNS use leads to the benefits of social support highlights the importance of these networks in providing increases in life quality. It has been largely proven that social support contributes to the positive adjustment and personal development as well as provides a buffer against stress (Sarason et al. 1983). Providing a platform for information exchange SNS and possibility to connect with similar others, SNS can thus provide support for those suffering from a wide variety of problems, such as chronic illnesses, depression, etc. However, as our findings show that only distinct types of their use can result in favorable outcomes for individuals in particular and society in general.

Limitations

The limitation of our study is the sample size mainly consisting of active Facebook users. Considering that Facebook gains popularity across other population segments, authors aim to validate the survey instrument with a more representative sample. Additionally, cluster analyses may be performed in order to identify specific user groups and the dynamics of their social capital formation.

In this study we only measure one structural quality of the network – network diversity in its impact on social capital benefits. This is bounded by the survey design and the methodology chosen which does not permit to explore the impact of both – tie strength as well as network redundancy – on the benefits of social capital. However, the findings we provide in section C3 show that these two factors have a diverging impact on information value, we expect similar effect to occur with other benefits of social capital: that is, stronger ties are better resources of social capital as well as more diverse and less redundant networks.

Another limitation of the study is that we tested the potential benefits of social capital and not the actual benefits that users get from their network. In this set-up we are bounded by the survey design, where most of the questions were directed at the network in general and not specific people in particular. In the next step this limitation can be overcome by conducting a study using by programming a similar application that is used in the section B3.2 and thus eliciting more objective responses from the users.

E Concluding Remarks

Coming back to the generic model depicted in Figure 4 and the research questions posed in Table 2 we can summarize the main conclusions of the dissertation. In most of the models we test we account for several variables out of the generic framework presented in Figure 4. The motivation behind exploring the impact of these factors is argued in the section A2. We show that there are significant interaction effects between these factors and researchers should not only focus on exploring the impact of one, without controlling for one or several of the others. For example, the factor of experience of using the medium in general and experience of communication with others in particular has emerged as a significant control in most variables we test. At the same time we find that tie strength with the people in the network largely determines the behavior of users on the network, i.e. how they process information and construct their networks. However, exploring such factors as social information and network overlap allowed us to gain more insights in the dynamics of user behavior on SNS. All in all, we confirm the applicability of the generic model and the overall framework we use in the dissertation. As a result, we can assess the role of SNS in increasing information value and generating social capital.

In the first part of the dissertation we explored two models: model B1 and B2. In the model B1 we mainly explored the impact of social information on information value, whereas controlling for tie strength as the network variable, post type as contextual property of information, frequency and duration of usage of the medium as experience of using the medium. The results of model B2 show that information characteristics, such as breadth and depth of information increase the value of information. Testing model B1 we also find that the opinions of the other users in the social environment play an important role in evaluating information. Their impact underlies quite interesting dynamics: although ratings positively impact information value, the impact of comments is rather negative due to the information overload they create. At the same time, the impact of social information differs depending on the tie strength with the user who is sharing the information. Thus, the weaker the relationship with the user, the more important becomes the impact of the social information. For the information from strongest ties, social information does not have any impact on evaluations at all. We also confirm the positive impact of the experience of using the medium and the experience of communicating with a communication partner on the value of information users derive from SNS. In the last step, we use the findings of the studies B1 and B2 to design an algorithm that filters the information for the user. We find that already by taking into account the objective factors to filter information, significant increases in prediction accuracy can be achieved. This highlights the fact that network providers should be careful when designing information filtering algorithms and conceptualize the inclusion of factors.

In the second part of the dissertation, we explored how users construct their networks as well as what impact the resulting network structure has on the value of information users derive from the platform. In the model C1 we explored the impact of social environment, intrinsic and extrinsic benefits on the willingness to send/accept a friendship request to people with various degrees of familiarity. In the model C2 we delineate the impact of two network properties - tie strength and network overlap on the informational

benefits users attain, whereby controlling for the social information and for the experience of actively using the platform for sharing information. Similar to the first part of the dissertation, we again show that depending on the strength of the tie, the network construction behaviors of users differ. That is, the stronger is the tie, the more willing are the people to include this person to the network. At the same time, different additional factors come into play when weighing the costs and the benefits of adding particular contacts, depending on the strength of the underlying relationship. As such, for stronger ties it is rather the social capital benefits that induce users to send friendship requests, whereas in case of new ties it is rather the intrinsic benefits that matter (having a more attractive profile for example). However, we also show that tie strength is not the only property of the network that impacts value. On the network level, the overlap of the network, although positively correlated with tie strength, has a negative impact on information value. Therefore, we provide evidence that both a strong connection to an individual and a relatively sparse network can be beneficial for information exchange.

In the third part of the dissertation we first identify the different types of SNS use (active participation, passive following, network construction and social browsing) as well as benefits of social capital resulting from SNS use. As our data shows the latter center around social support, participation and information value. In the next step, we first explore the direct impact of different types of SNS use on the benefits of social capital. In the next step, the sources of social capital – network structure and shared information – are introduced and their mediating role on the relationships between the types of use and benefits is proven. We find that not all types of SNS use directly lead to the benefits of social capital – where active participation is associated with most of the benefits, and social browsing of profiles of others does not result in any of the benefits. At the same time we show that it is rather the sources of social capital – shared information and network structure that trigger the attainment of the benefits of social capital. That is, the more diversified the network, the higher are the perceived social capital benefits, such as participation in more events, social support from others and information value. Similarly, the more valuable information users obtain from their networks, the more possibilities they have to develop relationships with others and gain social capital benefits. However, for some benefits such as social support, active participation still remains an active prerequisite of social capital gains.

We can summarize our findings into three main contributions:

- First and foremost, the underlying tie strength emerges as the most important factor that drives user behavior on SNS, what concerns both processing information and network construction. Therefore we confirm a so-called ‘relationship-primacy effect’: for strongest ties, no additional motivations are necessary to induce users to perform certain actions on the network. Only when tie strength is low, social information in form of ratings and comments is considered when processing information or other factors (such as expected social capital or intrinsic benefits such as self-presentation and curiosity) when deciding whether to integrate someone into the network. Therefore, when filtering information network providers should take the tie strength factor into account, which as our dissertation shows can be better determined by the similarity of interests between users rather than their communication intensity on the network.

- Second, although people prefer information from their stronger ties, researchers should differentiate between different forms of network structure in their impact on information value, as cohesion (exemplified by tie strength) and overlap of the network (proxied by the number of mutual friends). In fact, although these two properties are correlated, they have a totally different impact on information value: whereas tie strength is positively, network overlap is negatively associated with information value. The process of social capital formation uncovered in the dissertation also confirms this proposition: diversified network structure has a positive impact on the benefits of social capital. This shows that people do not only expect to gain social capital benefits from their strong ties, but recognize the potential of all ties in the network, where the diversity is encouraged and redundancy should be avoided.
- Third, experience factors mediate many of the behaviors of users on SNS. Most of the studies carried out in this dissertation show that the frequency and duration of SNS use is related to the increased value of information users obtain through these networks. However, the causality of this relationship is yet to be determined. It can be the case that the more frequent interaction with others through the medium helps to establish shared meaning with the members of the network and learn norms of overall communication through the medium, which as the Channel Expansion Theory suggests, will increase the capacity of the medium for rich interaction. Thus, people start processing information more easily from specific people and in general on the network and have enhanced ability to extract benefits from this information. Alternatively, those who extract more value from the information shared on the network, might be prone to use the network more frequently. What we, however, know is that not all types of network use lead to the same amount and type of social capital benefits, where more active uses of the network (such as sharing information and communication with others) are associated with more benefits of social capital as opposed to more passive ones (looking at what others share).

Relating to the role that SNS have in creating information value we stress the profound role of these networks in tailoring the information to the user's interests – the information that is exchanged either concerns user's friends or user's interests. Compared to other social media applications, on SNS information is based on real offline connections of individuals, as opposed to the ephemeral connections created on YouTube or Twitter. Thus, this information possesses the most value for the individuals, as well as allows to satisfy their curiosity and enriches transactive memory about others. We also find that, in contrast to the grim trends outlined by the researchers in the early 2000s relating to the decrease in social capital as a result of Internet use (Putnam 1995), our study shows that SNS results in increases in offline participation and social support – the two main premises of social capital.

At the same time, we show that SNS have their own caveats: the immense amount of information that is exchanged on these networks creates the feelings of information overload and impedes relationship development with others and the benefits that are associated with it. Thus, if users have not developed strat-

egies to construct their networks and to process the information, it is the role of the network providers to apply intelligent algorithms to filter the incoming information and to teach users how to filter information themselves. At the same time, in order to gain benefits, users have to be considerate when constructing their networks as well as actively participate and extract valuable knowledge from their network, not just passively follow the content of others.

However, the more experience users gain in communication on the network, the more they are able to assess the costs and the benefits of doing so and thus extract more value. As they gain experience with the medium, they learn what it can be best suited for and how best to use it, and thus their expectations are more objective and costs are easily assessed. As they gain experience in communication with others, they learn what others know and what they can learn from them and thus use this knowledge to increase the value of these contacts. Thus, we confirm the findings of the channel expansion theory (Carlson and Zmud 1999) for the case of SNS: the more users gain experience with SNS, the higher they perceive the value of the medium for information exchange and communication. Taken together, SNS can be useful in creating information value and social capital, if the necessary experience with the medium is achieved.

F References

- Ajzen, I. 1991. Theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50 (2), 179-211.
- Ajzen, I. 2001. Nature and Operation of Attitudes. *Annual Review of Psychology*, (52), 27-58.
- Ajzen, I. 2005. *Attitudes, personality, and behavior*, McGraw-Hill, New York.
- Ajzen, I. and Sexton, J. 1999. Depth of processing, belief congruence, and attitude-behavior correspondence. In *Dual-Process Theories in Social Psychology*, S. Chaiken and Y. Trope (eds.), The Guilford Press, New York.
- Aral, S. and Van Alstyne, M. 2011. The Diversity-Bandwidth Tradeoff. *American Journal of Sociology*, 117 (1), 90-171.
- Ariely, D. 2000. Controlling the Information Flow: Effects on Consumers' Decision Making and Preferences. *Journal of Consumer Research*, 27 (2), 233-248.
- Asvanund, A., K. Clay, R. Krishnan, M. D. Smith. 2004. An empirical analysis of network externalities in peer-to-peer music-sharing networks. *Information Systems Research*, 15 (2), 155-174.
- Bagozzi, R. and Baumgartner, H. 1994. The evaluation of structural equation models and hypothesis testing. In *Principles of Marketing Research*, R. Bagozzi (ed.), Cambridge, MA: Blackwell, pp. 386-422.
- Bakshy, E., Rosenn, I., Marlow, C., and Adamic, L. 2012. The Role of Social Networks in Information diffusion. Unpublished Manuscript available online at: <http://arxiv.org/abs/1201.4145>
- Bandura, A. 1977. *Social Learning Theory*, New York: General Learning Press.
- Bandura, A., McDonald, F. J. 1963. Influence of social-reinforcement and behavior of models in shaping children's moral judgments. *Journal of Abnormal Social Psychology*, 67 (3), 274-281.
- Barki, H. and Hartwick, J. 1989. Rethinking the concept of user involvement. *MIS Quarterly*, 13 (1), 53-63.
- Baron, R. M., and Kenny, D. A. 1986. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic and statistical considerations. *Journal of Personality and Social Psychology*, 51, 1173-1182.
- Baskerville, R., Lyytinen, K., Sambamurthy, V. and Straub, D. 2011. A response to the design-oriented information systems research memorandum. *European Journal of Information Systems*, 20, 11-15.
- Bederson, B.B. and Schneiderman, B. 2003. *The Craft of Information Visualization: Readings and Reflections*, Morgan Kaufmann Publishers, San Francisco, CA.
- Beer, D. 2008. Social Network(ing) Sites...Revisiting the Story so Far: A Response to danah boyd & Nicole Ellison. *Journal of Computer-Mediated Communication*, 13, 516-529.
- Berger, P. L., T. Luckmann. 1990. *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*, Anchor Books, New York.
- Bian, J., Agichtein, E., Liu, Y. and Zha, H. 2008. A Few Bad Votes Too Many? Towards Robust Ranking in Social Media. In *Proceedings of AIRWeb*, ACM Press, Beijing, China, pp. 53-60.

- Bickart, R.M. and Schindler, R.M. 2001. Internet forums as influential sources of consumer information. *Journal of Interactive Marketing*, 15 (3), 31 – 40.
- Bohner, G., Moskowitz, G. and Chaiken, S. 1995. The Interplay of Heuristic and Systematic Processing of Social Information. In *European Review of Social Psychology*, 6 (1), 33-68.
- Borgatti, S.P. 2005. Centrality and Network Flow. *Social Networks*, 27, 55-71.
- Borgatti, S.P., Mehra, A., Brass, D.J. and Labianca, G. 2009. Network Analysis in Social Sciences. *Science*, 323 (5916), 892-895.
- Bourdieu, P. 1985. The forms of capital. In *Handbook of Theory and Research for the Sociology of Education*, J. G. Richardson (ed.), Greenwood, New York, pp. 241-258.
- Boyd, D. 2006. Friends, Friendsters, and MySpace Top 8: Writing Community Into Being on Social Network Sites. In *First Monday*, 11 (12), available online at <http://www.danah.org/papers/FriendsFriendsterTop8.pdf>
- Boyd, D. 2008. Facebook's Privacy Trainwreck. *Convergence: The International Journal of Research into New Media Technologies*, 14 (1), 13-20.
- Boyd, D. 2010. Friendship. In *Hanging Out, Messing Around, Geeking Out: Living and Learning with New Media*, M. Ito, S. Baumer, M. Bittanti, D. Boyd, R. Cody, B. Herr, H.A. Horst, P.G. Lange, D. Mahendran, K. Martinez, C. Pascoe, D. Perkel, L. Robinson, C. Sims, L. Tripp, J. Antin, M. Finn, A. Law, A. Manion, S. Mitnick, D. Schlossberg and S. Yardi (eds.), Cambridge: MIT Press, pp. 79-116.
- Boyd, D. and Heer, J. 2006. Profiles as Conversation: Networked Identity Performance on Friendster. In *Proceedings of the 39th Hawaii International Conference on System Sciences*, Vol. 3, Kauai, HI, Washington, DC, USA: IEEE Computer Society, pp. 59-81.
- Boyd, D. M. and Ellison, N. B. 2008. Social Network Sites: Definition, History, and Scholarship. *Journal of Computer-Mediated Communication*, 13 (1), article 11.
- Breusch, T.S. and A.R. Pagan. 1979. A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47, 1287-1294.
- Burgoon, J.K. and Hale, J.L. 1987. Validation and Measurement of the fundamental themes of relational communication. *Communication Monographs*, 54, 307-324.
- Burke, M., Marlow, C. and Lento, T. 2009. Feed Me: Motivating newcomer contribution in SNS. In *Proceedings of the 27 International Conference on Human Factors in Computing Systems*, ACM Press, Boston MA, USA, pp. 945-954.
- Burke, M., Marlow, C., and Lento, T. 2010. Social Network Activity and Social Well-Being. In *Proceedings of the 28th International Conference on Human Factors in Computing Systems*, April 10-15, Atlanta, Georgia, USA.
- Burke, M., Kraut, R. and Marlow, C. 2011. Social Capital on Facebook: Differentiating Uses and Users. In *Proceedings of the Conference on Human Factors in Computing Systems (CHI 2011)*, Vancouver, BC, Canada, ACM Press, Boston, MA, USA.
- Burt, R.S. 1992. The Social Structure of Competition. In *Structural Holes*, Harvard University Press, pp. 57-87.
- Burt, R.S. 2001. Structural holes vs. network closure. In: *Social Capital: Theory and Research*, N.Lin, K.S. Cook, R.S. Burt (eds.), Vol 1, Aldine de Gruyter, pp. 31-56.

- Butler, J.S. and Moffitt, R. 1982. A computationally efficient quadrature procedure for the one-factor multinomial probit model. *Econometrica* (50), 761-764.
- Carlson, J.R. and Zmud, R.W. 1999. Channel Expansion Theory and the Experiential nature of media richness perceptions. *Academy of Management Journal*, 42 (2), 153-170.
- Carpenter, D., Esterling, K. and Lazer, D. 2003. The Strength of Strong Ties: A Model of Contact-Making in Policy Networks with Evidence from US Health Politics. *Rationality and Society*, 15 (4), 441 – 440.
- Carterette, B., Bennett, P. N., Chickering, D. M. and Dumais, S. T. 2008. Here or There Preference Judgments for Relevance. In *Proceedings of ECIR*, Lecture Notes in Computer Science, 4956, Springer Berlin-Heidelberg, pp. 16-27.
- Centola, D. and Macy, M. 2007. Complex Contagions and the Weakness of Long Ties. *American Journal of Sociology*, 94, 702-734.
- Chaiken, S. 1980. Heuristic Versus Systematic Information Processing and the Use of Source versus Message Cues in Persuasion. *Journal of Personality and Social Psychology*, 39 (5), 752-766.
- Chaiken, S. 1980. Heuristic Versus Systematic Information Processing and the Use of Source Versus Message Cues in Persuasion. *Journal of Personality and Social Psychology*, 39 (5), 752-766.
- Chaiken, S., Liberman, A. and Eagly, A. 1989. Heuristic and Systematic Processing Within and Beyond the Persuasion Context. In *Unintended Thought*, Uleman, J. and Bargh, J. (eds.), New York, pp. 212-252.
- Chen, H., Wigand, R. and Nilan, M. 2000. Exploring Web users' optimal flow experiences. *Information Technology & People*, 13 (4), 263–281.
- Chen, J., Geyer, W., Dugan, C., Muller, M., and Guy, I. 2009b. Make new friends, but keep the old: recommending people on social networking sites. In *Proceedings of the 27th International Conference on Human Factors in Computing Systems*, ACM Press, NY, pp. 201-210.
- Chen, J., Nairn, R. and Chi, E.H. 2011. Speak Little and Well: Recommending Conversations in Online Social Streams. In *Proceedings of the Conference on Human Factors in Computing System*, ACM Press, NY, pp. 217-226.
- Chen, J., Nairn, R., Nelson, L., Bernstein, M. and Chi, E.H. 2010. Short and Tweet: Experiments on Recommending Content from Information Streams. In *Proceedings of International Conference on Human Factors in Computing Systems*, ACM Press, NY, 1185-1194.
- Chen, Y., Shang, R-A. and Kao, C-Y. 2009a. The effects of Information Overload on consumers' subjective state towards buying decision in the Internet shopping environment. *Electronic Commerce Research and Applications*, 8, 48-58.
- Chin, W. W. 1998. The Partial Least Squares Approach to Structural Equation Modeling. In *Proceedings of Modern Methods for Business Research*, G. A. Marcoulides (ed.), Lawrence Erlbaum Associates, Mahwah, NJ, pp. 295-336.
- Cohen, J. 1988. *Statistical Power Analysis for the Behavioral Sciences*, Lawrence Erlbaum Associates, NJ: Hillsdale.
- Cohen, S., Mermelstein, R., Kamarck, T. and Hoberman, H.M. 1985. Measuring the Functional Components of Social Support. In *Social Support: Theory, Research, and Applications*, I.G. Sarason and B.R. Sarason (eds.), Dordrecht: Martinus Nijhoff Publishers, pp. 73-94.

- Coleman, J.S. 1988. Social Capital in the Creation of Human Capital. *American Journal of Sociology*, 94, 95-120.
- Constant, D., Sproull, L. and Kiesler, S. 1996. The Kindness of Strangers: The Usefulness of Electronic Weak Ties for Technical Advice. *Organization Science*, 7 (2), 119 – 135.
- Conway, M.M. 1985. *Political Participation in the United States*, Washington, D.C.: Congressional Quarterly.
- Crites, S.L., Fabriger, L.R., Petty, R.E. 1994. Measuring the Affective and Cognitive Properties of Attitudes: Conceptual and Methodological Issues. *Personality and Social Psychology Bulletin*, 20 (6), 619—634.
- Daft, R. L., Lengel, R. H., and Trevino, L. K. 1987. Message Equivocality, Media Selection, and Manager Performance: Implications for Information Systems. *MIS Quarterly*, 11 (3), 355-366.
- Daft, R.L. and Lengel, R.H. 1986. Organizational Information Requirements, Media Richness and Structural Design. *Management Science*, 32 (5), 554 – 571.
- Davis, F.D. 1989. Perceived usefulness, perceived ease of use, and user acceptance. *MIS Quarterly*, 13, 319–22.
- Davis, J.G. and Ganeshan, S. 2009. Aversion to Loss and information overload: An Experimental Investigation. In *Proceedings of the International Conference on Information Systems*, Phoenix, Arizona, USA, paper 11.
- Dellarocas, C. 2003. The digitalization of word of mouth: promise and challenges of online feedback mechanisms. *Management Science*, 49 (10), 1407-1424.
- Demuth, H., and Beale, M. 1997. *Matlab Neural Network Tool Box User's guide*, The Mathworks.
- Dennis, A.R. 1996. Information exchange in group decision making: you can lead a group to information, but you can't make it think. *MIS Quarterly*, 20 (4), 433 – 457.
- Dennis, A.R. and Kinney, S.T. 1998. Testing Media Richness Theory in the New Media: The Effects of Cues, Feedback, and Task Equivocality. *Information Systems Research*, 9 (3), 256 – 274.
- Donath, J. and Boyd, D. 2004. Public displays of connection. *BT Technology Journal*, 22 (4), 71-82.
- Driver, M.J. and Streufert, S. 1969. Integrative Complexity: an approach to individuals and groups as processing systems. *Administrative Science Quarterly* 14 (2), 272-285.
- Dunbar, R.I.M. 1992. Nercotex size as a constraint on group size in primates. *Journal of Human Evolution*, 20, 469 – 493.
- Eldon, E. 2010. Facebook's February 2010 US Traffic by Age and Sex: All Groups Growing, Men More Quickly. *InsideFacebook*, available online at: <http://www.insidefacebook.com/2010/03/01/facebook%E2%80%99s-february-2010-us-traffic-by-age-and-sex-all-groups-growing-men-more-quickly/>
- Ellison, N. B., Steinfield, C., and Lampe, C. 2007. The benefits of Facebook 'Friends': Social Capital and College Students' Use of Online Social Network Sites. *Journal of Computer-Mediated Communication*, 12 (4), article 1.
- Ellison, N. B., Steinfield, C., and Lampe, C. 2011. Connection strategies: social capital implications of Facebook-enabled communication practices. *New Media and Society*, 1, 1-20.

- Eppler, M.J. and Mengis, J. 2004. The Concept of Information Overload: A Review of Literature from Organization Science, Marketing, Accounting, MIS and related Disciplines. *The Information Society: An International Journal*, 20 (5), 1-20.
- Erickson, B. 1988. The relational basis of attitudes. In *Social structures: A network approach*, B. Wellman and S. Berkowitz (eds.), New York: Cambridge University Press, pp. 99–121.
- Facebook. 2011a. Facebook Statistics, available online at: <http://www.facebook.com/press/info.php?statistics>, retrieved on 01.05.2011.
- Facebook. 2011b. Facebook Query Language, available online at: <http://developers.facebook.com/docs/reference/fql/>
- Facebook. 2012. Facebook Statistics, available online at: <http://www.facebook.com/press/info.php?statistics>
- Falk, R. F., and Miller, N.B. 1992. *A primer for Soft Modeling*, The University of Arkon Press, Ohio.
- Feldman, P. and Cohen, S. 2000. Social Support. In *Encyclopedia of Psychology*, A. E. Kadzin (ed.), Oxford University Press, New York, pp. 373-376.
- Festinger, L. 1954. A theory of social comparison processes. *Human Relations*, 7 (2), 117—140.
- Fischer, C.S. 1982. *To Dwell Among Friends*, Chicago: University of Chicago Press.
- Fishbein, M. and Ajzen, I. 1975. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*, Reading, MA: Addison-Wesley.
- Fiske, S.T. and Taylor, S.E. 1991. *Social cognition, 2d Edition*. New York: McGraw-Hill.**
- Fitzsimmons, C. 2010a. Coca-Cola Marketing Event Tracked Facebook Users via RFID. [allfacebook.com](http://www.allfacebook.com/coca-cola-marketing-2010-08), available online at: <http://www.allfacebook.com/coca-cola-marketing-2010-08>.
- Fitzsimmons, C. 2010b. Now QR Codes can Generate Likes on Facebook. [allfacebook.com](http://www.allfacebook.com), available online at: <http://www.allfacebook.com/qr-codes-facebook-2010-08>.
- Fitzsimmons, C. 2010c. Facebook and Amazon Join Forces for Social Shopping. [allfacebook.com](http://www.allfacebook.com), available online at: <http://www.allfacebook.com/facebook-amazon-recommendations-201007>.
- Fitzsimmons, C. 2010d. “Urban Outfitters Now Judging Clothing Popularity Based on “Likes,” [allfacebook.com](http://www.allfacebook.com), available online at: <http://www.allfacebook.com/urban-outfitters-likes-2010-08>.
- Fornell, C. G., and Larcker, D.F. 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18 (3), 39-50.
- Fornell, C., and Bookstein, F. L. 1982. Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory. *Journal of Marketing Research*, 19, 440-452.
- Friedman, H.H. and Amoo, T. 1999. Rating the rating scales. *Journal of Marketing Management*, 9 (3), 114-123.
- Fulk, J., J. Schmitz, C. Steinfield. 1990. A social influence model of technology use. In *Organizations and Communication Technology*, J. Fulk and C. Steinfield (eds.), Sage, Newbury Park, CT, pp. 117–142.
- Fulk, J., Steinfield, C., Schmitz, J., Power, J.G. 1987. A social information processing model of media use in organizations. *Communication Research*, 14 (5), 529 – 552.

- Gallaugh, J. & Ransbotham, S. 2010. Social media and customer dialog management at Starbucks. *MIS Quarterly Executive*, 9 (4), 197-212.
- Garfinkel, H. 1967. *Studies in Ethnomethodology*, Prentice-Hall, Englewood Cliffs, NJ.
- Gershoff, A., Mukherjee, A. and Mukhopadhyay, A. 2003. Consumer acceptance of online agent advice: extremity and positivity effects. *Journal of Consumer Psychology*, 13, 161 – 170.
- Ghoshal, S., Korine, H., Szulanski, G. 1994. Interunit communication in multinational corporations, *Management Science*, 40, 96 -110.
- Gilbert, E. and Karahalios, K. 2009. Predicting Tie Strength with Social Media. In *Proceedings of the 27th International Conference on Human Factors in Computing Systems*, ACM Press, NY, pp. 211-220.
- Glaser, B. 1992. *Basics of grounded theory analysis*, Mill Valley, CA: The Sociology Press.
- Glynn, C.J., Huge, M.E. and Hoffman, L.H. 2012. All the news that's fit to post: A profile of news use on Social Networking Sites. *Computers in Human Behavior*, 28, 113-119.
- Granovetter, M.S. 1973. The Strength of Weak Ties, *American Journal of Sociology*, 78 (6), 1360-1380.
- Greene, W. H. 2000. *Econometric Analysis*, Prentice Hall, New Jersey, pp. 875-878.
- Hair, J. F., Anderson, R. E., Tatham, R. L., and Black, W. C. 1998. *Multivariate data analysis with readings*, Englewood Cliffs, Prentice-Hall.
- Hallinan, M. T. 1978-1979. The process of friendship formation. *Social Networks*, 1 (2), 193-210.
- Hansen, M. T. 2002. Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science*, 13 (3), 232-248.
- Hansen, M. T. and Haas, M. R. 2001. Competing for attention in knowledge markets: Electronic document dissemination in a management consulting company. *Administrative Science Quarterly*, 46 (1), 1-28.
- Hansen, M.T. 1999. The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge across Organization Subunits. *Administrative Science Quarterly*, 44 (1), 82 – 111.
- Hansman, K. W., and Ringle, C. M. 2005. Strategische Erfolgswirkung einer Teilnahme an Unternehmensnetzwerken: eine Empirische Untersuchung. *Die Unternehmung*, 59 (3), 217-236.
- Härdle, W.K. and Simar, L. 2007. *Applied Multivariate Statistical Analysis*, 2nd edition, Springer.
- Hausman, J. A. 1978. Specification Tests in Econometrics. *Econometrica*, 46 (6), 1251–1271.
- Haythornwaite, C. 2002. Strong, Weak, and Latent Ties and the Impact of New Media. *The Information Society*, 18, 385-401.
- Henseler, J., Ringle, C., and Sinkovics, R. 2009. The Use of Partial Least Squares Modeling in International Marketing. *Advances in International Marketing*, 20, 277-319.
- Herlocker, J.L., Konstan, J.A., Terveen, L.G. and Riedl, J.T. 2004. Evaluating Collaborative Filtering Recommender Systems. *ACM Transactions on Information Systems*, 22 (1), 5-53.
- Hevner, A.R., March, S.T., Park, J. and Ram, S. 2004. Design Science in Information Systems Research. *MIS Quarterly*, 28 (1), 75-105.

- Hill, W. and Terveen, L. 1996. Using frequency-of-mention in public conversations for social filtering. In *Proceedings of the ACM conference on Computer-Supported Cooperative Work*, pp. 106-112.
- Hogben, G. 2007. Security Issues and Recommendations for Online Social Networks. *ENISA Position Paper*, available online at: <http://www.ifap.ru/library/book227.pdf>
- Homburg, C., and Baumgartner, H. 1995. Beurteilung von Kausalmodellen – Bestandsaufnahme und Anwendungsempfehlungen. *Marketing ZFP*, 17 (3), 162-176.
- Homburg, C., and Giering, A. 1996. Konzeptualisierung und Operationalisierung komplexer Konstrukte. *Marketing-Zeitschrift für Forschung und Praxis*, 18, 5-24.
- Hu, L., and Bentler, P. M. 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6 (1), 1-55.
- Hulland, J. 1999. Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies. *Strategic Management Journal*, 20, 195-204.
- IJsselstein, W., van Baren, J., Markopoulos, P., Romero, N. and de Ruyter, B. 2009. Measuring affective benefits and costs of mediated awareness: Development and validation of the ABC-Questionnaire. In *Awareness Systems: Advances in theory, methodology and design*, P. Markopolous, B. de Ruyter and W. Mackay (eds.), Springer, London, pp. 473 - 488.
- Johnston, W.A. and Dark, V.J. 1986. Selective Attention. *Annual Review of Psychology*, 37, 43-75.
- Joinson, A. N. 2008. 'Looking at', 'Looking up' or 'Keeping up with' People? Motives and Uses of Facebook. In *Proceedings of the 26th annual SIGCHI conference on Human factors in computing systems*, Florence, Italy, pp. 1027-1036.
- Jones, Q., Moldovan, M., Raban, D., and Butler, B. 2008. Empirical Evidence of Information Overload Constraining Chat Channel Community Interactions. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work*, ACM Press, NY, 323-332.
- Jones, Q., Ravid, G. and Rafaeli, S. 2004. Information Overload and Message Dynamics of Online Interaction Spaces: A Theoretical Model and Empirical Exploration. *Information Systems Research*, 15 (2), 194-210.
- Kane, G. C. and Fichman, R. G. 2009. The shoemaker's children: using Wikis for IS research, teaching, and publication. *MIS Quarterly*, 33(1), 1-22.
- Kane, G.C., Alavi, M., Labianca, J. and Borgatti, P. 2012. Social Media Networks: A Research Agenda. Forthcoming in *MIS Quarterly*.
- Kincaid, J. 2010. EdgeRank: The Secret Sauce that makes Facebook's Newsfeed Tick. *TechCrunch*, available online at: <http://techcrunch.com/2010/04/22/facebook-edgerank/>
- Köbler, F., Riedl, C., Vetter, C., Leimeister, J.M., and Krcmar, H. 2010. Social Connectedness on Facebook – An Explorative Study on Status Message Usage. In *Proceedings of the Sixteenth Americas Conference on Information Systems*, Lima, Peru, paper 247.
- Kokkinaki, F. and Lunt, P. 1999. The effect of advertising message involvement on brand attitude accessibility. *Journal of Economic Psychology*, 20, 41-51.
- Kolenikov, S., and Angeles, G. 2004. The Use of Discrete Data in Principal Component Analysis With Applications to Socio-Economic Indices. In *Proceedings of the Joint Statistical Meeting*, 1-10.

- Konstan, J.A., Miller, B.N., Maltz, D., Herlocker, J.L., Gordon, L.R. and Riedl, J. 1997. GroupLens: Applying collaborative filtering to Usenet news. *Communications of the ACM*, 40 (3), 77-87.
- Koroleva, K., Krasnova, H. and Günther, O. 2010. 'STOP SPAMMING ME!' – Exploring Information Overload on Facebook. In *Proceedings of the Americas Conference on Information Systems*, Lima, Peru, paper 447.
- Koroleva, K., Krasnova, H. and Günther, O. 2011a. Cognition or Affect? – Exploring Information Processing on Facebook. In *Proceedings of the Third International Conference on Social Informatics (SocInfo'11)*, Springer-Verlag Berlin, Heidelberg, pp. 171-183.
- Koroleva, K., Krasnova, H., Veltri, N. and Günther, O. 2011c. It is all about Networking! – Empirical Investigation of Social Capital Formation on Social Network Sites. In *Proceedings of International Conference on Information Systems*, Shanghai, China, paper 24.
- Koroleva, K., Stimac, V., Krasnova, H. and Kunze, D. 2011b. I like it because I('m) like you – Measuring User Attitudes Towards Information on Facebook. In *Proceedings of the International Conference on Information Systems*, Shanghai, China, paper 26.
- Krackhardt, D. 1992. The Strength of Strong Ties: The Importance of Philios in Organizations. In *Networks and Organizations*, Nohria and R. G. Eccles (eds.) Cambridge, MA: Harvard Business School Press, pp. 216-239.
- Krasnova, H., Kolesnikova, E., and Günther, O. 2009a. It Won't Happen To Me!: Self-Disclosure in On-line Social Networks. In *Proceedings of the 15th Americas Conference on Information Systems*, San Francisco, USA, paper 343.
- Krasnova, H., Günther, O., Spiekermann, S. and Koroleva, K. 2009b. Privacy Concerns and Identity in Online Social Networks. *Identity in the Information Society*, 2 (1), pp. 39-63.
- Krasnova, H., Spiekermann, S., Koroleva, K. and Hildebrand, T. 2010a. Online Social Networks: Why We Disclose. *Journal of Information Technology*, 25 (2), 109-125.
- Krasnova, H., Kolesnikova, E. and Günther, O. 2010b. Leveraging Trust and Privacy Concerns in Online Social Networks: an Empirical Study. In *Proceedings of the European Conference on Information Systems*, Pretoria, South Africa, paper 160.
- Krasnova, H., Koroleva, K., and Veltri, N. 2010c. Investigation of the Network Construction Behavior on Social Networking Sites. *Proceedings of the International Conference on Information Systems (ICIS 2010)*, AIS Electronic Library, Paper 182.
- Kraut, R.E., Rice, R.E., Cool, C. and Fish, R.S. 1998. Varieties of social influence: the role of utility and norms in the success of a new communication medium. *Organization Science*, 9 (4), 437 - 452.
- Kruglanski, A. 1975. The Human Subject in the Psychology Experiment: Fact and Artifact. In *Advances in Experimental Social Psychology*, L. Berkowitz (ed.), Orlando: Academic Press, pp. 101 -147.
- Kutner, N.N. 2004. *Applied Linear Regression Models*, 4th edition, McGraw-Hill Irwin.
- Lampe, C., Ellison, N., and Steinfield, C. 2006. A Face(book) in the Crowd: Social Searching vs. Social Browsing. In *Proceedings of the 20th anniversary conference on Computer Supported Cooperative Work*, pp. 167-170.
- Lampe, C., Vitak, J., Gray, R. and Ellison, N.B. 2012. Perceptions of Facebook's Value as an Information Source. In *Proceedings of the ACM Conference on Human Factors in Computing Systems*, Austin, Texas, USA, pp. 3195-3204.

- Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D. and Van Alstyne, M. 2009. Life in the network: the coming age of computational social science. *Science*, 323 (5915), 721 - 723.
- Lewis, J. and West, A. 2009. 'Friending': London-based undergraduates' experience of Facebook. *New Media & Society*, 11 (7), 1209-1229.
- Livingstone, S. 2008. Taking risky opportunities in youthful content creation: teenagers' use of social networking sites for intimacy, privacy and self-expression. *New Media and Society*, 10 (3), 393-411.
- Loewenstein, G. 1994. The Psychology of Curiosity: A review and reinterpretation. *Psychological Bulletin*, 116 (1), 75-98.
- MacFadden, D.L. 1974. *Conditional Logit Analysis of Qualitative Choice Analysis Frontiers in Econometrics*, New York: Academic Press, pp. 105-142.
- Madge, C., Meek, J., Wellens, J. and Hooley, T. 2009. Facebook, social integration and informal learning at university: 'It is more for socializing and talking to friends about work than for actually doing work'. *Learning, Media, & Technology*, 34 (2), 141-155.
- Maheswaran, D. and Chaiken, S. 1991. Promoting Systematic Processing in Low-Motivation Settings: Effect of Incongruent Information on Processing and Judgment. *Journal of Personality and Social Psychology*, 61 (1), 13-25.
- March, S.T. and Smith, G.F. 1995. Design and Natural Science Research on Information Technology. *Decision Support Systems*, 15, 251-266.
- Mardsen, P.V. and Campbell, K.E. 1984. Measuring Tie Strength. *Social Forces* (83), 482 – 501.
- Matavire, R. and Brown, I. 2008. Investigating the Use of Grounded Theory in Information Systems Research. In *ACM International Conference Proceeding Series of the SAICSIT*, Wilderness, South Africa, New York ACM, pp. 139-147.
- McGuire, W.J. 1976. Some internal psychological factors influencing consumer choice. *Journal of Consumer Research*, 2 (4), 302-319.
- McPherson, M., Smith-Lovin, L. and Cook, J. 2001. Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, 27 (1), 415-444.
- Miller, G.A. 1956. The magical number seven, plus or minus two: some limits to our capacity for processing information. *Psychological Review*, 2, 81-97.
- Miranda, S.M. and Saunders, C.S. 2003. The Social Construction of Meaning: An Alternative Perspective on Information Sharing. *Information Systems Research*, 14 (1), 87 – 106.
- Morris, M.R., Teevan, J., and Panovich, K. 2010. What do people ask their social network and why? A survey study of status message Q&A behavior. In *Proceedings of the ACM Conference on Human Factors in Computing Systems*, Atlanta, USA, pp. 1739-1748.
- Morrison, C. 2010. Facebook's June 2010 US Traffic by Age and Sex: Users Aged 18-44 Take a Growth Break. *InsideFacebook*, available online at: <http://www.insidefacebook.com/2010/07/06/facebook-june-2010-us-traffic-by-age-and-sex-users-aged-18-44-take-a-break-2/>
- Muise, A., Christofides, E., and Desmarais, S. 2009. More Information than You Ever Wanted: Does Facebook Bring Out the Green-Eyed Monster of Jealousy? *CyberPsychology & Behavior*, 12 (4), 441-444.

- Nahapiet, J. and Ghoshal, S. 1998. Social Capital, Intellectual Capital, and the Organizational Advantage. *Academy of Management Review*, 23 (2), 242-266.
- Nie, N.H. 2001. Sociability, Interpersonal Relations and the Internet. *American Behavioral Scientist*, 45 (3), 420 - 435.
- Northrup, L. 2009. Facebook, Where are you getting these crazy friend suggestions from? *The Consumerist*, available online at: <http://consumerist.com/2009/06/facebook-where-are-you-getting-these-crazy-friend-suggestions-from.html>
- Nunnally, J. C. 1978. *Psychometric Theory*, New York, McGraw-Hill.
- O'Keeffe, G. S., Clarke-Pearson, K., and Council on Communications and Media. 2011. Clinical Report, The Impact of Social Media on Children, Adolescents, and Families, Pediatrics. *Pediatrics*, 127 (4), 800-804.
- Oh, H., Labianca, G., and Chung, M. H. 2006. A multilevel model of group social capital. *Academy of Management Review*, 31 (3), 569-582.
- Orlikowski, W. 1993. CASE tools are organizational change: Investigating Incremental and Radical Changes in Systems Development. *MIS Quarterly*, 17 (3), 309-340.
- Pace, S. 2004. A grounded theory of the flow experiences of Web users. *International Journal of Human-Computer Studies*, 60 (3), 327-363.
- Paek, T., Gamon, M., Counts, S., Chickering, D.M. and Dhesi, A. 2010. Predicting the Importance of Newsfeed Posts and Social Network Friends. In *Proceedings of the 24th AAAI Conference on Artificial Intelligence*, available online at: [http://research.microsoft.com/pubs/135702/1878-8304-1-pb\[1\].pdf](http://research.microsoft.com/pubs/135702/1878-8304-1-pb[1].pdf).
- Pazzani, M. J., Muramatsu, J., and Billsus, D. 1996. Syskill webert: Identifying interesting web sites. In *Proceedings of the 13th National Conference on Artificial Intelligence*, 1, pp. 54-61.
- Pearlman, L. 2009. I Like This. *The Facebook Blog*, available online at: <http://blog.facebook.com/blog.php?post=53024537130>.
- Pempek, T., Yermolayeva, Y. and Calvert, S. 2009. College students' social networking experiences on Facebook. *Journal of Applied Developmental Psychology*, 30 (3), 227-238.
- Pickering, J.L. and King, J.L. 1995. Hardwiring weak ties: interorganizational computer-mediated communication, occupational communities, and organizational change. *Organization Science*, 6 (4), 479 - 486.
- Portes, A. 1998. Social capital: its origins and applications in modern sociology. *Annual Review of Sociology*, 24, 1-24.
- Procidano, M. E., and Heller, K. 1983. Measures of perceived social support from friends and from family: three validations studies. *American Journal of Community Psychology*, 11 (1), 1-24.
- Putnam, R. 1995. Bowling alone: America's Declining Social Capital. *Journal of Democracy*, 6 (1), 65-78.
- PWC Study. 2012. Social media Deutschland: "The winner takes it all". *PricewaterhouseCoopers AG*, available online at: <http://www.pwc.de/de/corporate-governance/social-media-jeweils-eine-plattform-fuehrend.jhtml>.

- Rainio, K. 1966. A study of sociometric group structure: an application of a stochastic theory of social interaction. In *Sociological Theories in Progress*, J. Berger, M. Zelditch and B. Anderson (eds.), Boston: Houghton Mifflin, pp. 456-478.
- Reagans, R. and McEvily, B. 2003. Network Structure and Knowledge Transfer: the Effects of Cohesion and Range. *Administrative Science Quarterly*, 48, 240-267.
- Reagans, R. and Zuckerman, E. 2001. Networks, Diversity, and Productivity: The social Capital of corporate R&D teams. *Organization Science*, 12 (4), 502-517.
- Renner, B. 2006a. Social Curiosity Scale (English Version), available online at http://www.unikonstanz.de/diagnostik/dl_mess/scs_engl.pdf.
- Renner, B. 2006b. Curiosity about people: The development of a measure of social curiosity in adults. *Journal of Personality Assessment*, 87 (3), 305-316.
- Resnick, P. 2001. Beyond Bowling Together: SocioTechnical Capital. In *HCI in the New Millenium*, J. Carroll (ed.), MA: Addison-Wesley, Boston, pp. 247-272.
- Ringle, C. M. 2004. Gütemaße für den Partial Least Squares-Ansatz zur Bestimmung von Kausalmodellen. In *Institute of Industrial Management*, University of Hamburg, paper 16.
- Ringle, C. M., Wende, S., and Will, A. 2005. SmartPLS, Release 2.0.M3. University of Hamburg. Hamburg, Germany, available online at: <http://www.smartpls.de>
- Rowley, T., Behrens, D., and Krackhardt, D. 2000. Redundant governance structures: An analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic Management Journal*, 21 (3), 369-386.
- Sachoff, M. 2011. Most Women Annoyed By Facebook Friends. Available online at: <http://www.webpronews.com/most-women-annoyed-by-facebook-friends-2011-03>
- Salancik, G.R. and Pfeffer, J. 1978. A Social Information Processing Approach to Job Attitudes and Task Design. *Administrative Science Quarterly*, 23, 224 – 253.
- Sandberg, S. 2009. How many friends can you have? *The Facebook Blog*, available online at: <http://blog.facebook.com/blog.php?post=72975227130>.
- Sarason, I.G., Levine, H.M., Basham, R.B., and Sarason, B.R. 1983. Assessing social support: The social support questionnaire. *Journal of Personality and Social Psychology*, 44 (1), 127-139.
- Saucier, G. 1994. Mini-markers: A brief version of Goldberg's unipolar Big-Five markers. *Journal of Personality Assessment*, 63 (3), 506-516.
- Schick, A., Gordon, L.A., Haka, S. 1990. Information Overload: A temporal approach. *Accounting, Organisation and society*, 15 (3), 119-220.
- Schmitz, J. and Fulk, J. 1991. Organizational colleagues, media richness and electronic mail – a test of the social influence model of technology use. *Communication Research*, 18 (4), 487-523.
- Schneider, S.C. 1987. Information Overload: causes and consequences. *Human Systems Management*, 7, 143-153.
- Schöndienst, V. and Dang-Xuan, L. 2012. '...A friend indeed?' An empirical analysis of interactions in online social networks. In *Proceedings of the European Conference on Information Systems (ECIS 2012)*, paper 234.

- Schroder, H.M., Driver, M.J. and Steufert, S. 1967. *Human information processing - Individuals and Groups functioning in complex social situations*, New York: Holt, Rinehart & Winston.
- Schultz, U. and Vandebosch, B. 1998. Information overload in a groupware environment: now you see it, now you don't. *Journal of Organizational Computing and Electronic Commerce*, 8 (2), 127 – 148.
- Schutz, A. 1997. *Phenomenology of the Social World*, Northwestern University Press, Evanston, IL.
- Seidel, S. and Recker, J. C. 2009. Using grounded theory for studying business process management phenomena. In *Proceedings of the 17th European Conference on Information Systems*, Verona, Italy, paper 137.
- Shah, D.V., Kwak, N. and Holbert, R.L. 2001. "Connecting" and "Disconnecting" with civic life: Patterns of Internet Use and Production of Social Capital. *Political Communication*, 18 (2), 141-162.
- Short, J., Williams, E., & Christie, B. 1976. *The social psychology of telecommunications*, London: Wiley.
- Sicilia, M. and Ruiz, S. 2010. The effects of the amount of information on cognitive responses in online purchasing tasks. *Electronic Commerce Research and Applications*, 9 (2), 183-191.
- Smith, J. 2009a. Facebook Reoptimizes Friends Page for Growth, Friend List Creation. insidefacebook.com, available online at <http://www.insidefacebook.com/> 2009/04/30/facebook-reoptimizes-friends-page-for-growth- friend-list-creation/.
- Smith, J. 2009b. Fastest Growing Demographic on Facebook: Women Over 55", insidefacebook.com, available online at <http://www.insidefacebook.com/> 2009/02/02/fastest-growing-demographic-on-facebook-women-over- 55/.
- Sobel, M. E. 1982. Asymptotic confidence intervals for indirect effects in structural equations models. In *Sociological methodology*, S. Leinhardt (ed.), San Francisco: Jossey-Bass, pp. 290-312.
- Sproull, L. and Kiesler, S. 1986. Reducing social context cues: electronic mail in organizational communication. *Management Science*, 32 (11), 1492 - 1512.
- Strauss, A. and Corbin, J. 1998. *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*, Sage Publications Inc.
- Sundar, S. and Nass, C. 2001. Conceptualizing Sources in Online News. *Journal of Communication*, 51 (1), 52-72.
- Sundar, S., Knobloch-Westerwick, S., Hastall M. 2007. News Cues: Information Scent and Cognitive Heuristics. *Journal of the American Society for Information Science and Technology*, 58 (3), 366-378.
- Swedberg, R. 1990. *Economics and Sociology*, Princeton University Press.
- Thelwall, M. 2008. Social networks, gender, and friending: An analysis of MySpace member profiles. *Journal of the American Society for Information Science and Technology*, 59 (8), 1321-1330.
- Thomas, J. and Griffin, R. 1983. The social information model of task design: a review of the literature. *Academy of Management Review*, 8 (4), 672-682.
- Thorngate, W. 1997. More than we can know: The attentional economics of internet use. In *Culture of the Internet*, Kiesler, S. (ed.), Lawrence Earlbaum Associates, Mahwah, NJ, pp. 296–297.

- Tom Tong S., Van der Heide, B., and Langwell L. 2008. Too much of a good thing? The relationship between number of friends and interpersonal impressions on Facebook. *Journal of Computer-Mediated Communication*, 13, 531-549.
- Tonkelowitz, M. 2011. Interesting News, Any Time You Visit. *The Facebook blog*, available online at: <http://blog.facebook.com/blog.php?post=10150286921207131>
- Trevino, L., Daft, R., and Lengel, R. 1990. Understanding managers' media choices: A symbolic interactionist perspective. In *Organizations and communication technology*, J. Fulk and C. Steinfield (eds), Newbury Park, CA: Sage, pp. 71-94.
- Trevino, L.K. and Webster, J. 1992. Flow in computer-mediated communication. *Communication Research*, 19 (5), 539 - 573.
- Tufekci, Z. 2008. Gender, Social Capital And Social Network(ing) Sites: Women Bonding, Men Searching. In *Annual Meeting of the American Sociological Association Annual Meeting*, Boston, MA, available online at: http://citation.allacademic.com/meta/p_mla_apa_research_citation/2/4/2/6/9/p242696_index.html
- Turow, J. 2006. *Niche Envy: Marketing Discrimination in the Digital Age*, Cambridge, MA: The MIT Press.
- Uzzi, B. 1997. Social structure and competition in inter-firm networks: The paradox of embeddedness. *Administrative Science Quarterly*, 42, 35-67.
- Valenzuela, S., Park, N. and Kee, K.F. 2009. Is There Social Capital in a Social Network Site? Facebook Use and College Students' Life Satisfaction, Trust, and Participation. *Journal of Computer-Mediated Communication*, 14, 875-901.
- Verba, S., Schlozman, K.L., and Brady, H.E. 1995. *Voice and Inequality: Civic voluntarism in American politics*, Cambridge, MA: Harvard University Press.
- Vitak, J., Ellison, N. B., and Steinfield, C. 2011. The Ties that bond: re-examining the relationship between Facebook Use and Bonding Social Capital. In *Proceedings of the 44th Annual Hawaii International Conference on System Sciences*, Computer Society Press, pp. 1-10.
- Voss, K., Spangenberg, E. and Grohmann, B. 2003. Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude. *Journal of Marketing Research* 40 (3), 310-320.
- Walther, J.B. 1992. Interpersonal effects in computer-mediated interaction: A relational perspective. *Communication Research*, 19 (1), 52-90.
- Walther, J.B. 1995. Relational Aspects of Computer-Mediated Communication: Experimental Observations over Time. *Organization Science*, 6 (2), 186-203.
- Walther, J.B. and Burgoon, J.K. 1992. Relational Communication in Computer-Mediated Communication. *Human Communication Research*, 19 (1), 50-88.
- Webster, J., and Trevino, L. 1995. Rational and social theories as complementary explanations of communication media choices: Two policy-capturing studies. *Academy of Management Journal*, 38, 1544-1572.
- Weick, K.E. 1985. Cosmos vs. chaos: Sense and nonsense in electronic contexts. *Organizational Dynamics*, 14 (2), 51-64.
- Wellman, B., Haase, A.Q., Witte, J. and Hampton, K. 2001. Does the Internet Increase, Decrease, or Supplement Social Capital? *American Behavioral Scientist*, 45 (3), 436-455.

- White, H. 1982. Maximum likelihood estimation of misspecified models. *Econometrica*, 50, 1-25.
- Williams, D. 2006. On and Off the 'Net: Scales for Social Capital in an Online Era. *Journal of Computer-Mediated Communication*, 11 (2), 593-628.
- Wilson, R.E., Gosling, S.D. and Graham, L.T. 2012. A Review of Facebook Research in the Social Sciences. Forthcoming in *Perspectives on Psychological Science*.
- Wood, W., Kallgreen, C.A. and Preisler, R.M. 1985. Access to Attitude-Relevant Information in Memory as a Determinant of Persuasion: The Role of Message Attributes. *Journal of Experimental Social Psychology*, 21, 73-85.
- Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data*, MIT Press.
- Wright, P. H. 1978. Toward a theory of friendship based on a conception of self. *Human Communication Research*, 4 (3), 196-207.
- Xu, X., Dinev, T., Smith, H. and Hart, P. 2008. Examining the Formation of Individual's Privacy Concerns: Toward an Integrative View. In *Proceedings of the 29th International Conference on Information Systems*, paper 6.
- Yang, H. and Yoo, Y. 2004. It's all about attitude: revisiting the technology acceptance model. *Decision Support Systems*, 38, 19-31.
- Yoo, Y. and Alavi, M. 2001. Media and group cohesion: relative influences on social presence, task participation, and group consensus. *MIS Quarterly*, 25 (3), 371 – 390.

G Appendices

Appendix 1. Strategies and Actions of Dealing with Information Overload

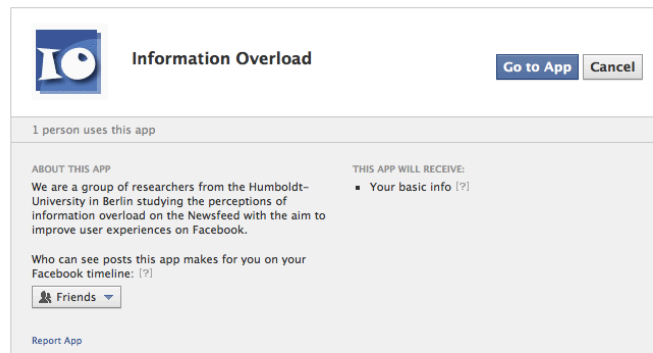
<i>passive</i>	Cognitive heuristics	<p>Friend-based: <i>"Usually I start with checking my close friends, or the people I like most... And then I check what else is going on"</i></p> <p>Distance-based: <i>"It would be the other way round when I am in India, I would definitely give preferences to my friends who are in Germany because you want to know more about them since you're not with them"</i></p> <p>Information-based: <i>"This could be something more interesting because she is talking about classes or some event they are planning, so it's interesting for me to look at it"</i></p> <p>Explicit: <i>"I have my criteria, I will not click on the videos, especially if they are longer than one minute"</i></p> <p>Self-centered: <i>"I'm going through the whole as I said, but not as much as I check and expect comments to my pictures"</i></p>
	Omission	<i>"It's boring. I just start sometimes, and I don't even finish, because I am not interested in this guy, what he is doing"</i>
	Failed action	<i>"I did not hide all those application things, although they don't apply to me at all"</i>
<i>active</i>	Hiding people/information	<i>"I just go and hide the people because I really don't want updates about them"</i>
	Deleting people/information	<i>"And what I also regularly do, I check my friends list and I delete people "</i>
	Account deactivation	<i>"I can deactivate it, so it can keep me from logging back in, because some things really irritate me, especially if you see them every day"</i>
<i>advanced</i>	Ex-ante network control	<i>"I want to keep the number of people limited, because then in the Newsfeed you have lots of stuff from people you don't even know"</i>
	Control of self-behavior	<i>"I try not to share that much information, so that it's not polluted"</i>

Appendix 2. Survey Items for Studies B1 and B2

Construct	Question	Answer Options
Affective Value	How do you feel about this post?	(i) <i>like very much – like – slightly like – slightly dislike – dislike – dislike very much</i> (ii) <i>very interesting – quite interesting – slightly interesting – slightly boring – quite boring – very boring</i>
Instru-mental Value	How do you evaluate this post?	(i) <i>very useful – quite useful – slightly useful – slightly useless – quite useless – very useless</i> (ii) <i>very relevant – quite relevant – slightly relevant – slightly irrelevant – quite irrelevant – very irrelevant</i>
Behavioral Intention	How would you approach this post?	<i>read/look and consider commenting – read/look and consider liking – read attentively (and view comments) – give a brief look – ignore – ignore and consider hiding</i>
Compre-hensibility	Do you understand this post? - language of the post - meaning of the post	<i>very well – more or less – not at all</i>
Posting Frequency	How much does this person post on Facebook? How often do you see posts from this person on Facebook?	(i) <i>very much – quite a lot – somewhat – not that much – not much at all</i> (ii) <i>almost always – regularly – every once in a while – rarely – almost never/not at all</i>
Tie Strength	How well do you know this person?	<i>very well – quite well – slightly know – hardly know – don't know at all</i>
Similarity	How much do you have in common with this person?	<i>very much in common – quite a lot – something – hardly anything – nothing at all</i>
Communi-cation In-tensity	How often do you communicate with the person through Facebook? - private communication - public communication - following on Facebook	<i>almost always – regularly – every once in a while – rarely – almost never/not at all</i>
Location	Where is this person located at the moment?	<i>in the same city – in another city, but in the same country – in another country – on another continent – I am not sure</i>

Appendix 3. Application Design for Studies B1 and B2

Stage 1. Application Invitation.



Information Overload Go to App Cancel

1 person uses this app

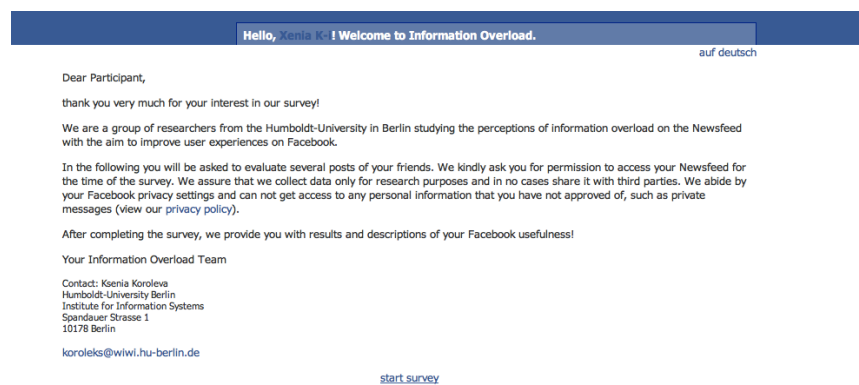
ABOUT THIS APP
We are a group of researchers from the Humboldt-University in Berlin studying the perceptions of information overload on the Newsfeed with the aim to improve user experiences on Facebook.

THIS APP WILL RECEIVE:
▪ Your basic info [?]

Who can see posts this app makes for you on your Facebook timeline: [?]
Friends

[Report App](#)

Stage 2. Welcome.



Hello, Xenia K! Welcome to Information Overload. auf deutsch

Dear Participant,

thank you very much for your interest in our survey!

We are a group of researchers from the Humboldt-University in Berlin studying the perceptions of information overload on the Newsfeed with the aim to improve user experiences on Facebook.

In the following you will be asked to evaluate several posts of your friends. We kindly ask you for permission to access your Newsfeed for the time of the survey. We assure that we collect data only for research purposes and in no cases share it with third parties. We abide by your Facebook privacy settings and can not get access to any personal information that you have not approved of, such as private messages (view our [privacy policy](#)).

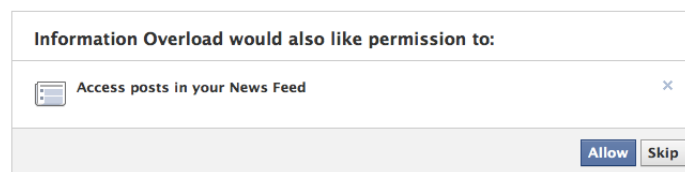
After completing the survey, we provide you with results and descriptions of your Facebook usefulness!

Your Information Overload Team


Contact: Ksenia Koroleva
Humboldt-University Berlin
Institute for Information Systems
Spandauer Strasse 1
10178 Berlin
koroleks@wwi.hu-berlin.de

[start survey](#)

Stage 3. Permissions.

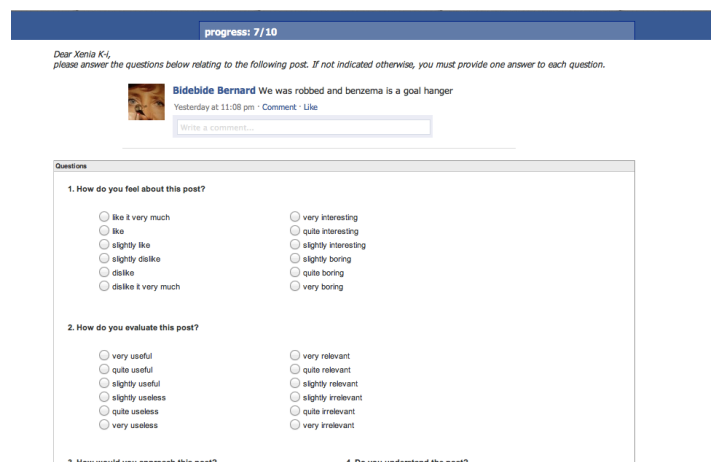


Information Overload would also like permission to:

 **Access posts in your News Feed** ×


Allow Skip

Stage 4. Please answer the questions about the following post



progress: 7/10

Dear Xenia K-1,
please answer the questions below relating to the following post. If not indicated otherwise, you must provide one answer to each question.

 **Bidebide Bernard** We was robbed and benzema is a goal hanger
Yesterday at 11:08 pm · Comment · Like

Write a comment...

Questions

1. How do you feel about this post?

<input type="radio"/> like it very much	<input type="radio"/> very interesting
<input type="radio"/> like	<input type="radio"/> quite interesting
<input type="radio"/> slightly like	<input type="radio"/> slightly interesting
<input type="radio"/> slightly dislike	<input type="radio"/> slightly boring
<input type="radio"/> dislike	<input type="radio"/> quite boring
<input type="radio"/> dislike it very much	<input type="radio"/> very boring

2. How do you evaluate this post?

<input type="radio"/> very useful	<input type="radio"/> very relevant
<input type="radio"/> quite useful	<input type="radio"/> quite relevant
<input type="radio"/> slightly useful	<input type="radio"/> slightly relevant
<input type="radio"/> slightly useless	<input type="radio"/> slightly irrelevant
<input type="radio"/> quite useless	<input type="radio"/> quite irrelevant
<input type="radio"/> very useless	<input type="radio"/> very irrelevant

3. How would you approach this post? 4. Do you understand this post?

Appendix 4. Estimation Results of the full Ordered Probit Regression³⁴

Variable	Affective	Cognitive
<i>Word count</i>	0.007 (0.00) **	0.010 (0.003) ***
<i>Word count squared</i>	-0.000 (0.00)	-0.000 (0.00) **
<i>Affirmations</i>	0.042 (0.01) ***	0.038 (0.01) ***
<i>Comments</i>	-0.016 (0.01) **	-0.021 (0.01) **
<i>Photos (w.r.t status)</i>	0.329 (0.11) ***	0.389 (0.11) ***
<i>Links (w.r.t status)</i>	0.045 (0.08)	0.483 (0.09) ***
<i>Understandability</i>	0.730 (0.08) ***	0.633 (0.085) ***
<i>Similarity</i>	0.552 (0.11) ***	0.463 (0.11) ***
<i>Public Communication</i>	0.161 (0.13)	0.326 (0.13) **
<i>Private Communication</i>	0.299 (0.13) **	0.087 (0.13)
<i>Passive Following</i>	0.479 (0.11) ***	0.274 (0.11) **
<i>Posting Frequency</i>	-0.171 (0.08) **	-0.164 (0.08) **
<i>Location</i>	0.106 (0.09)	-0.001 (0.092)
<i>Pseudo-R²</i>	10%	7.6%

Appendix 5.Application Design for Study C2

³⁴ - ***-1%, **5%, standard error in brackets. As users evaluated information on an ordinal scale, we estimate an Ordered Probit regression (Greene, 2000) tailored to use with the dependent variables of this type. Moreover, as each respondent evaluated six different posts, we apply a panel-data specification via the inclusion of user-specific random effects (Buttler and Moffitt, 1982). The dependent variables are the different dimensions of user evaluations – affective, instrumental and cognitive, whereas the independent – the information and relationship characteristics. In order to standardize the independent variables (as they were measured on ordinal scales), we create dummy variables, which are equal to one for the high levels of these variables, and zero in all other cases. We determine the split of the variables into high vs. low levels based on the median of the sample. For post type, we explore the impact of links and pictures with respect to status updates. We add word count squared as we hypothesize that the number of words will have an inverted u-shape relationship with user evaluations.

Stage 1. Welcome

Hello, Xenia K-I Welcome to Information Overload. [auf deutsch](#)

Dear Participant,

thank you very much for your interest in our survey!

We are a group of researchers from the Humboldt-University in Berlin studying the perceptions of information overload on the Newsfeed with the aim to improve user experiences on Facebook.

In the following you will be asked to evaluate several posts of your friends. We kindly ask you for permission to access your Newsfeed for the time of the survey. We assure that we collect data only for research purposes and in no cases share it with third parties. We abide by your Facebook privacy settings and can not get access to any personal information that you have not approved of, such as private messages (view our privacy policy).

After completing the survey, we provide you with results and descriptions of your Facebook usefulness!

Your Information Overload Team

Contact: Xenia Koroleva
Humboldt-University Berlin
Institute for Information Systems
Spandauer Chausse 1
10178 Berlin
koroleva@wiwi.hu-berlin.de

[start survey](#)

Stage 2. Permissions

facebook [Search for people, places and things](#) Xenia K-I Home

IO2 would like permission to:

Access the following required information:


- Your profile info: description, activities, birthday, education history, groups, hometown, interests, likes, location, relationship status, relationship details and work history
- Your events
- Your photos
- Friends' profile info: descriptions, Activities, birthdays, education histories, groups, hometowns, interests, likes, locations, relationship statuses, relationship details and work histories
- Events shared with you
- Photos shared with you


Access posts in your News Feed



[Allow](#) [Cancel](#)

Stage 3. Choose posts on the Newsfeed that you would pay attention to.

Dear Xenia K-I,
Please select the posts from your Newsfeed which you would pay attention to:

☐  Mehran Palad is going to *** feestje van de kwart-eeuw *** — Saturday, July 7 at 6:00pm at stadhouderskade 57, amsterdam.
Like · Comment · Yesterday at 9:17 pm




☐  Cathe Rojas commented on a photo.
Like · Comment · Yesterday at 10:27 pm

☐  Boiler Room
Look what Pioneer just sent us! Could this be the end of our 'technical'? Probably not but it'll make things better for sure.

Like · Comment · 613 68 · Yesterday at 11:24 pm

☐  Patty Chuang updated her current city to Durham, North Carolina.
Like · Comment · 10 hours ago
1 people like this.

Stage 4. Choose the friends that one knows well/would like to get to know better.

Dear Xenia K-I,
Please select the friends you ...

	know well	would like to get to know better
	<input type="checkbox"/>	<input type="checkbox"/>
	<input type="checkbox"/>	<input type="checkbox"/>
	<input type="checkbox"/>	<input type="checkbox"/>

Appendix 6. Survey Items for Study C1

Construct / Source	Survey Items	Measure-ment Scale
<i>Likelihood of Accepting FR: Once you have received a FR, how likely are you to accept it from: Likelihood of Sending a FR: How likely are you to search for and send a FR on FB to:</i>		
Strong Ties (self-developed)	1. ... someone you know well from university; 2. ... an old acquaintance; 3. ... a good friend from childhood; 4. ...someone you worked tightly with on the same project; 5. ... someone you meet at sport every week.	
Weak Ties (self-developed)	1. ... someone you visit a course with but do not really know well; 2. ...someone you have met once at a conference; 3. ...someone you have talked to at a party; 4. ... someone you had an interesting conversation with on the train.	
No Relationship (self-developed)	1. ... someone you don't know but who has one mutual friend with you on FB; 2. ...someone you don't know but whose profile is interesting for you (interesting CV, interesting country of origin, etc...); 3. ...someone you heard a lot about but did not have a chance to meet; 4. ...someone you don't know but who has something in common with you (same school, work); 5. ...someone you don't know but who has several mutual friends with you on FB; 6. ...someone you don't know but with whom you have common interests (similar hobbies, music tastes, favorite movies).	1 – very unlikely . .. 7 – very likely
<i>Independent Variables:</i>		
Social Capital (based on Williams, 2006)	1. Based on the people I interact with on Facebook it is easy for me to hear about new job opportunities 2. Through the people I interact with on Facebook it is easy for me to find out useful information; 3. If I need to, I can ask my Facebook friends to put me in contact with someone important for me; 4. The people I interact with on Facebook help me stay in touch with what is new and popular	1 – strongly disagree . . .
Peer Pressure	1. I often feel obligated to add a particular contact; 2. It would be rude to reject a friendship request; 3. It is just polite to accept a friendship request if you get one; 4. If someone I know, but don't really like, sends me a friend's request I will be polite and accept it.	. . . 7- strongly agree
Self-Presentation (self-developed)	Having a lot of friends in my profile: 1. ... lets me have more weight in the eyes of others; 2. ... makes my profile look more trustworthy to others; 3. ... makes me feel good; 4. ... enhances my reputation/status among Facebook users; 5. ... makes my profile look more interesting and appealing to others.	
Curiosity	Items: 1, 2, 3, 6, 7, 10 of the Social Curiosity Scale by Renner (2006a).	

Control	How much control do you have on Facebook (e.g. through functionality, privacy options/policies) over:	1 – no control at
(based on Krasnova et al. (2010b))	1. ...who can collect and use the information you provide; 2. ...what information is accessible to whom; 3. ...the actions of other users (e.g. tagging you in pictures, writing on your or their Wall, etc.); 4. ...the information other users can communicate about you on Facebook (by writing on your wall, commenting on your and their photos, tagging you etc.).	all . . .7 – full control
Social Norm (self-developed)	On Facebook it is common: 1. ...to accept friendships' requests; 2. ...to look for and add new friends; 3. ... to try to make as many friendships as possible; 4. ...to get to know new people.	1 – strongly disagree . .
Privacy Management	1. The more friends I have on Facebook, the more I have to control what I reveal about myself; 2. The more friends I have on Facebook, the more I have to think what I post; 3. Having many friends on Facebook hinders my self-expression; 4. The more friends I have on Facebook, the less I can treat Facebook as a private space	. . . 7- strongly agree

Appendix 7. Emerging Categories in Qualitative Analysis

	Construct	Initial Codes	Freq.³⁵
ACTIONS	Following	Checking Newsfeed; checking photos; checking profiles; selecting information to read; hiding posts from the Newsfeed	50; 14
	Posting	Sharing experiences; communicating personal news; sharing traditional information; sharing joys and sorrows; asking questions; managing information disclosure; blocking contacts	61; 14
	Reciprocal Communication	<i>Direct</i> : sending and receiving messages, using chat <i>Indirect</i> : commenting, liking, Wall, stream communication General: selective communication, reciprocity	68; 14
	Network Construction	Adding new contacts, reacting to friend requests, sending friend requests, adding people suggested by Facebook, deleting people	37; 14
SOURCES	Network Structure	<i>Size</i> : Amount of friends, distance of friends, expanding network, new contacts <i>Structure</i> : diversifying network, satisfaction with the network, people from other backgrounds	61; 14
	Shared Information	<i>Staying in touch</i> : being connected, feeling close, being remembered, staying in touch, expectation of communication, increased communication <i>Informational</i> : current information, interest in information, keeping up to date with friends, learning more about friends	198; 14
BENEFITS	Participation	<i>Events</i> : participating in more offline events, getting more invitations, diversified events <i>Friends</i> : arranging offline meetings with friends, developing relationships, expectation of relationship	50; 14
	Informational	<i>Broadening Horizons</i> : learning new things, broadening horizons, belonging to a broader group <i>Getting useful information</i> : feeling informed, getting useful information, intangible (informational) favors	37; 14
	Social Support	<i>Emotional</i> : Feeling supported by friends, seeking emotional support, getting relief <i>Instrumental</i> : Tangible favors, getting advice, asking for help, putting in contact with someone	46; 14
CONTEXT	Functionality	Technical features, group communication, effortless communication	29; 14
	Social Norm	Ease of communication, ease of finding people, informal communication	21; 14
	Tie Strength	Quality of friendship, affection level, communication intensity, common friends, common ground, common interests	63; 14

³⁵ - 1st - the number of times this category was mentioned in all interviews/observations;

2nd - the number of participants mentioning this category (out of 14)

Appendix 8. Rotated Component Matrix of EFA Actions

Item	1	2	3	4	5
P1: Post something	.863	.183	.039	.062	.066
P2: Share thoughts and feelings	.844	.119	.080	.065	.065
P3: Share something you are interested in	.860	.084	.070	.103	-.028
P4: Share your impressions with your friends	.842	.133	.155	.031	.083
C1: React to what friends post	.695	.318	.104	.031	.278
C2: Comment on what friends post	.730	.353	.004	.091	.340
C3: Like what friends post * ³⁶	.597	.423	.109	.037	.309
C4: Send private messages *	.090	.277	.148	-0.39	.709
C5: Chat *	.233	-0.025	.039	.089	.805
F1: Follow the news of your friends	.298	.719	.124	.090	.145
F2: Look through the Newsfeed	.219	.821	-.070	-.012	-.007
F4: Click on the content shared by friends	.186	.730	.165	.092	.124
F3: Browse the profiles of your friends	.159	.360	.635	-.012	.193
N3: Browse through friends of your friends	.106	-.036	.855	.217	.037
N4: Look at profiles of people not in the list	.084	.045	.843	.180	.042
N1: Search for people to add	-.054	-.007	.341	.775	.025
N2: Send friendship requests	.131	.122	.104	.738	.152
N5: Add people suggested by Facebook	.123	.024	.014	.792	-.094

Identified Factors:

1 - Active Participation

2 - Passive Following

3 - Social Browsing

4 - Network Construction

5 - Private Communication

³⁶ - Items marked with * were removed after the EFA

Appendix 9. Rotated Component Matrix of EFA Social Capital Benefits and Sources

Items	1	2	3	4	5
SS1: I can count on my Facebook friends when things go wrong	.162	.061	.778	.093	.132
SS2: I do not hesitate to ask people in my list to do smth. for me	.130	.149	.769	.136	.151
SS3: I can easily ask people in my contact list for a small favor	.022	.214	.711	.163	.135
SS4: When I have a bad day, I turn to my friends on Facebook	.219	.049	.691	.111	.148
Now that I use Facebook,					
OP1: I take part in more social events	.156	-0.006	.180	.436	.693
OP2: I participate in events that I would not do otherwise	.162	-0.120	.158	.361	.688
OP3: ... I have a chance to see my friends more often in person	.109	.300	.198	-.013	.745
OP4: ... I arrange to meet my friends more frequently	.094	.367	.174	.003	.750
Interacting with people on Facebook,					
HB1: ... makes me want to try new things	.287	.080	.222	.693	.242
HB2: ... makes me curious about other places in the world	.202	.236	.049	.683	.142
HB3: ... I get useful information	.228	.324	.238	.656	.123
HB4: ... I learn new things	.209	.251	.139	.697	.039
Through Facebook, I ...					
SC1: ... find out what my friends are up to	.111	.811	.083	.198	.024
SC2: ... am updated about my friends	.199	.740	.084	.211	.003
SC3: ... stay in touch with my friends	.162	.639	.203	.134	.303
SC4: ... interact with my friends more	.159	.639	.181	.201	.330
NS1: ...expand my circle of friends netw	.711	.130	.211	.183	.119
NS2: ...communicate with a broader range of people	.757	.168	.099	.128	.155
NS3: ...diversify my circle of acquaintances	.799	.055	.112	.187	.171
NS4: ...interact with a wider variety of people than offline	.738	.321	.145	.152	-.032
NS5: ...come in contact with people different from myself	.781	.060	.088	.230	.084

Identified Factors:

- 1 – Network Structure
- 2 – Shared Information,
- 3 – Social Support
- 4 – Information Benefits
- 5 - Participation

Appendix 10. Other publications not included into this dissertation

Topic	Title	Status
Journal publications on topic of the Dissertation	Koroleva, K., Stimac, V. and Kane, G.C. 2012. The Role of Tie Strength in Determining the Value of Information on Social Network Sites. Submitted to Management Science.	submitted
	Krasnova, H., Koroleva, K., Kane, G.C., Veltri, N. Social Capital on Social Network Sites (working title). In preparation for MISQ.	in preparation
Teenagers' Social Network Site Use	Koroleva, K., Brecht, F., Göbel, L. and Malinova, M. 2011. 'Generation Facebook' – A Cognitive Calculus Model of Teenage User Behavior on Social Network Sites. Proceedings of the Americas Conference on Information Systems (AMCIS 2011), AIS Electronic Library, paper 392. Best Paper Award.	published
	Koroleva, K. and Göbel, L. Generation Facebook (working title). In preparation for JAIS.	in preparation
Bounded Rationality	Brecht, F., Günther, O., Güth, W. and Koroleva, K. 2012. An Experimental Analysis of Bounded Rationality Regarding risk, time and social preferences. In preparation.	in preparation
	Koroleva, K., Brecht, F., Güth, W. and Günther, O. 2012. Prospect Theory: Empirical Evidence and its Application to Privacy Issues in IS. In Review for ICIS 2012.	submitted
Employer Branding	Brecht, F., Koroleva, K. and Günther, O. 2011. Increasing the Global Reach: Using Social Network Sites for Employer Branding. Wirtschaftsinformatik Proceedings, AIS Electronic Library, Paper 17.	published

Acknowledgements

First of all, I would like to thank my first adviser – Prof. Oliver Günther – for the possibility to complete this dissertation, for the exciting times at the Institute, for the general guidance and for the financing of the numerous conference trips.

I would like to express my sincere gratitude to my second adviser – Prof. Jerry Kane – for the scientific guidance, for the exciting discussions to the core of the theory and the challenges of discovery!

For the methodological guidance and substantial contribution to this dissertation I am very grateful to my friend and co-author Vid Stimac with whom we have spent sleepless nights: *“Assaulting Newsfeed spam, one partial derivative at a time”* (Stimac 2010).

I would like to thank my co-author and colleague Hanna Krasnova for bringing me in, for the valuable guidance during my first years and several years of fruitful collaboration exploring Social Network Sites.

Also I would like to thank my friend, co-author and colleague Franziska Brecht for her operative support and other exciting projects!

More than to anyone else I am grateful to my dad for the inspiration to become a scientist and my mom, for guiding me in the western direction. But I think it was meant to be, as.... since the earliest years of my life I could not decide whether I liked Socrates or Aristotle more ☺...

Last but not least, a big hug to my family & friends – Artiom Chaplygin, Patricia Diniz, Elena Silyakova, Maria Grith, Alexandra Fedorets, Jens Malling, Christopher Lansloot, Erik Fasten, Valentin Schöndienst - for their moral support and inspiration, especially in the last months of preparing this dissertation!

Selbstständigkeitserklärung

Hiermit erkläre ich, die vorliegende Arbeit selbstständig ohne fremde Hilfe verfasst und nur die angegebene Literatur und die angegebenen Hilfsmittel verwendet zu haben.

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, den 29.06.2012

Ksenia Koroleva